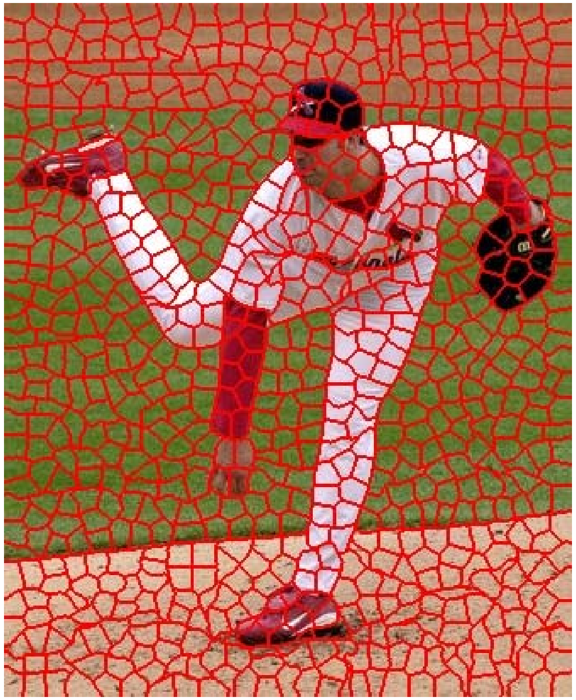
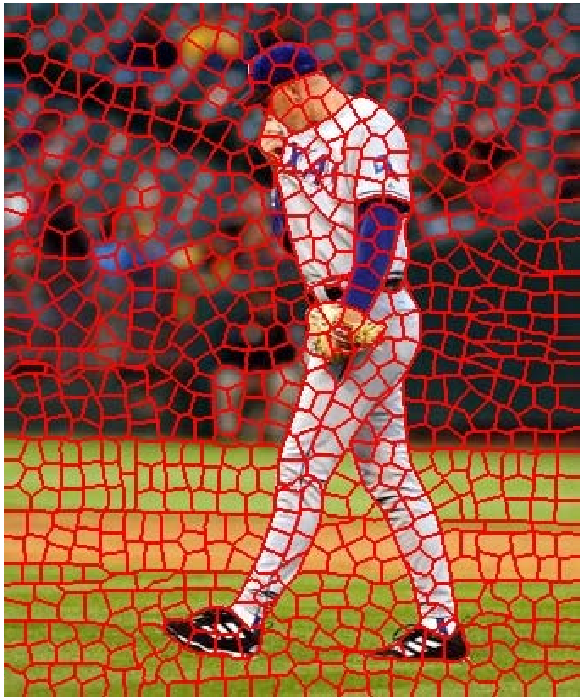
Image segmentation

The goals of segmentation

- Group together similar-looking pixels for efficiency of further processing
  - “Bottom-up” process
  - Unsupervised

“superpixels”





X. Ren and J. Malik. [Learning a classification model for segmentation.](#) ICCV 2003.

The goals of segmentation

- Separate image into coherent “objects”
  - “Bottom-up” or “top-down” process?
  - Supervised or unsupervised?

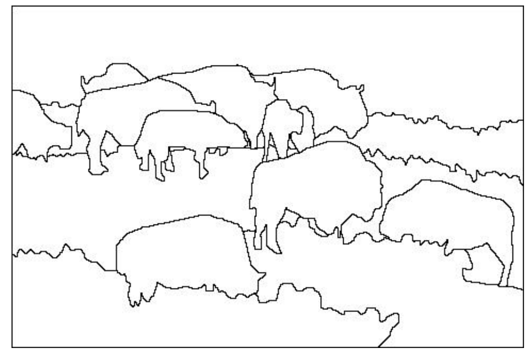
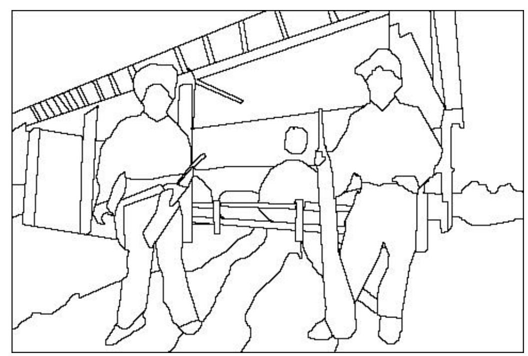


image | human segmentation



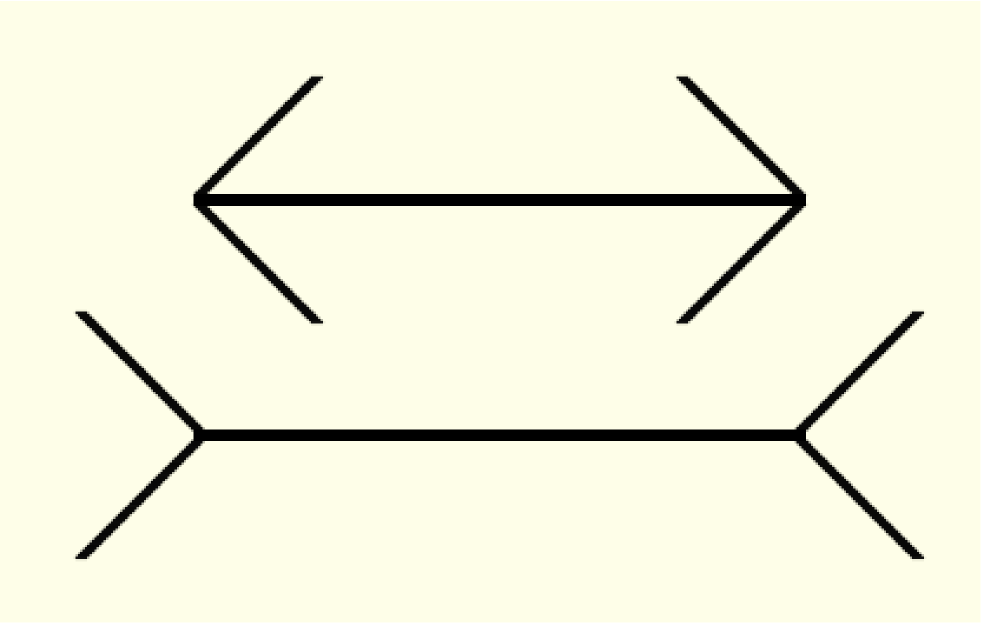
Berkeley segmentation database:

http://www.eecs.berkeley.edu/Research/Projects/CS/vision/grouping/segbench/

Inspiration from psychology

- The Gestalt school: Grouping is key to visual perception

The Muller-Lyer illusion



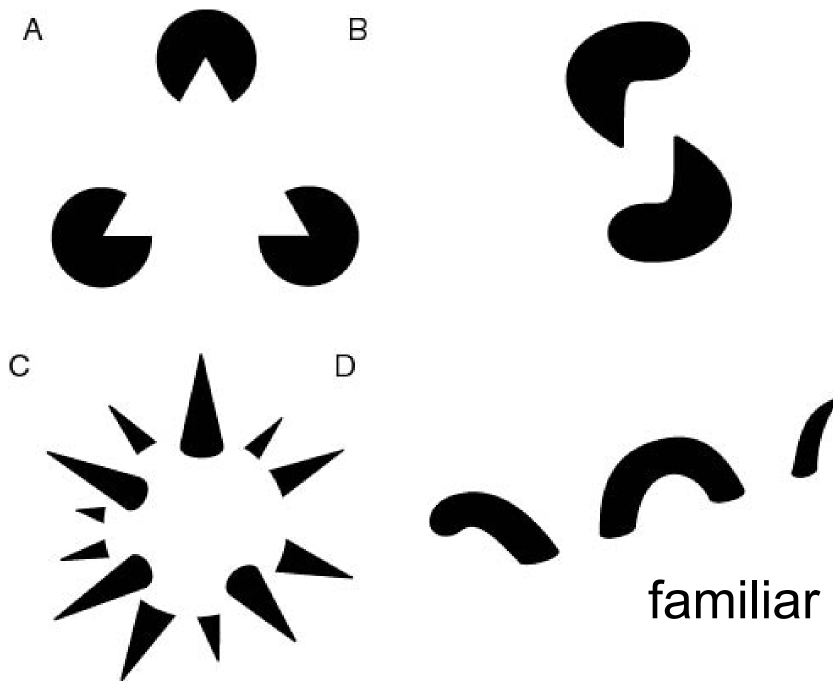
http://en.wikipedia.org/wiki/Gestalt_psychology

The Gestalt school

- Elements in a collection can have properties that result from relationships
  - “The whole is greater than the sum of its parts”

subjective contours

occlusion



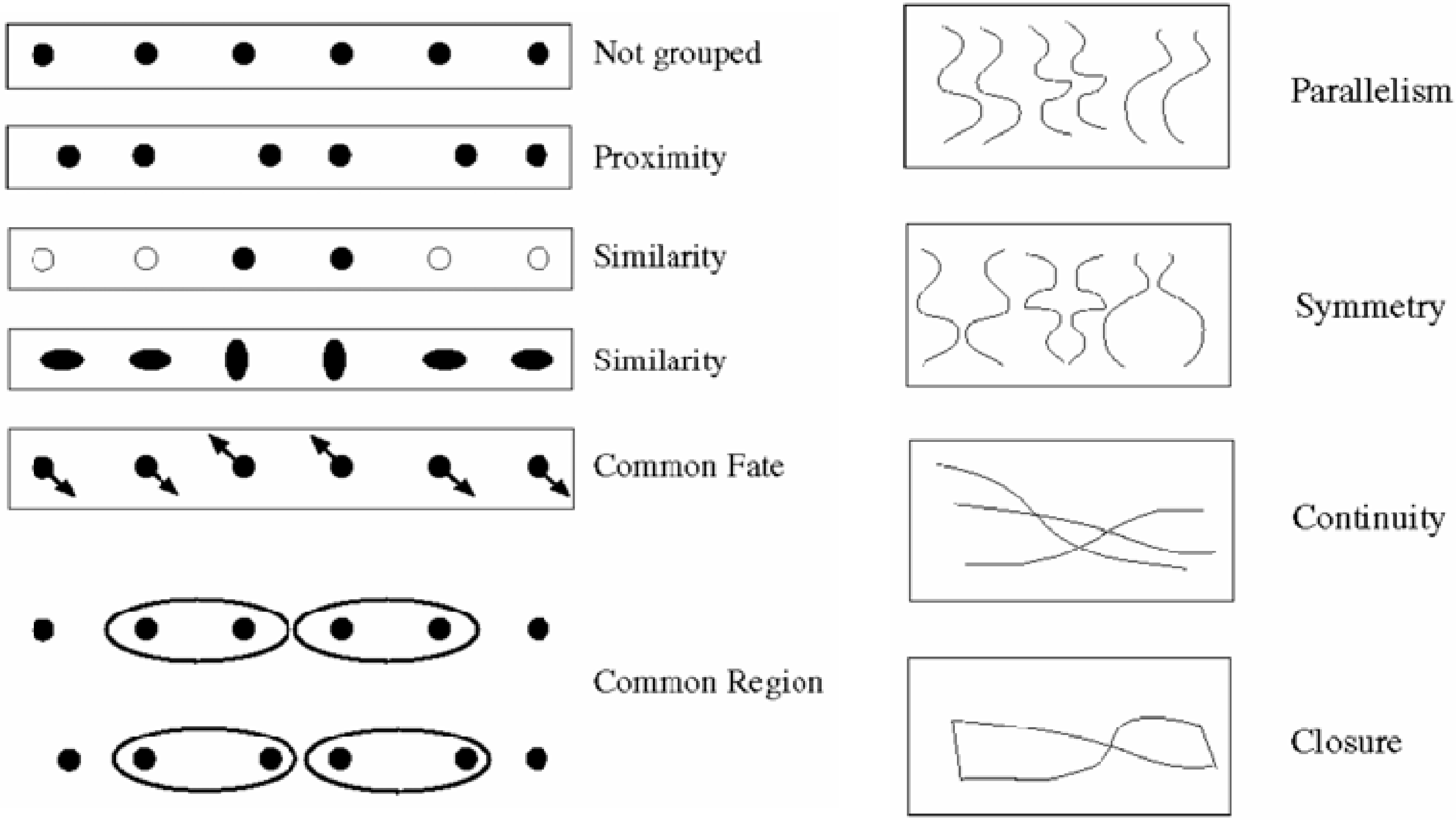
familiar configuration

http://en.wikipedia.org/wiki/Gestalt_psychology

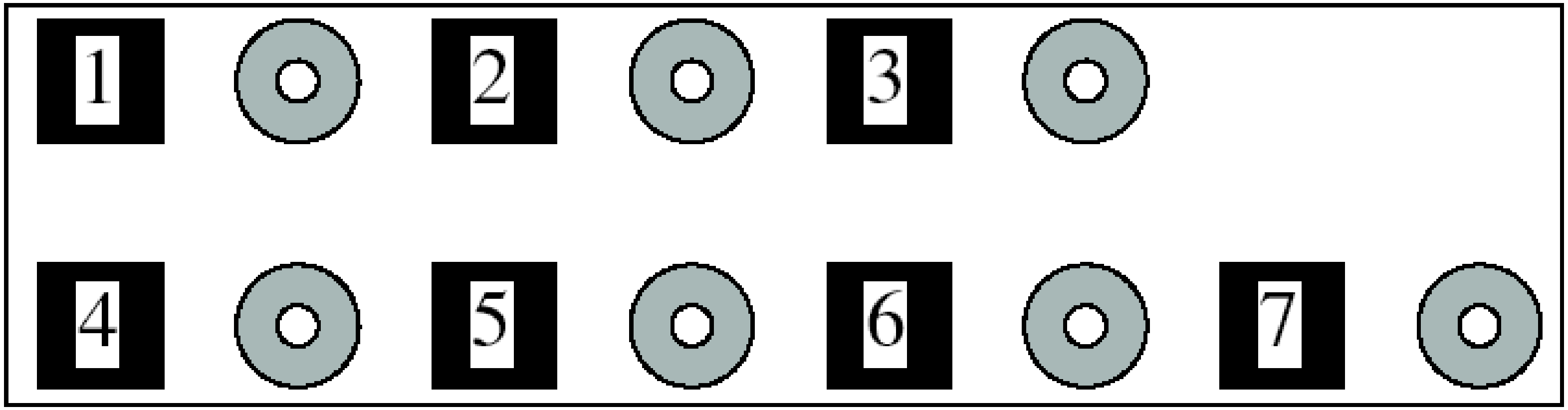
Emergence

http://en.wikipedia.org/wiki/Gestalt_psychology

Gestalt factors

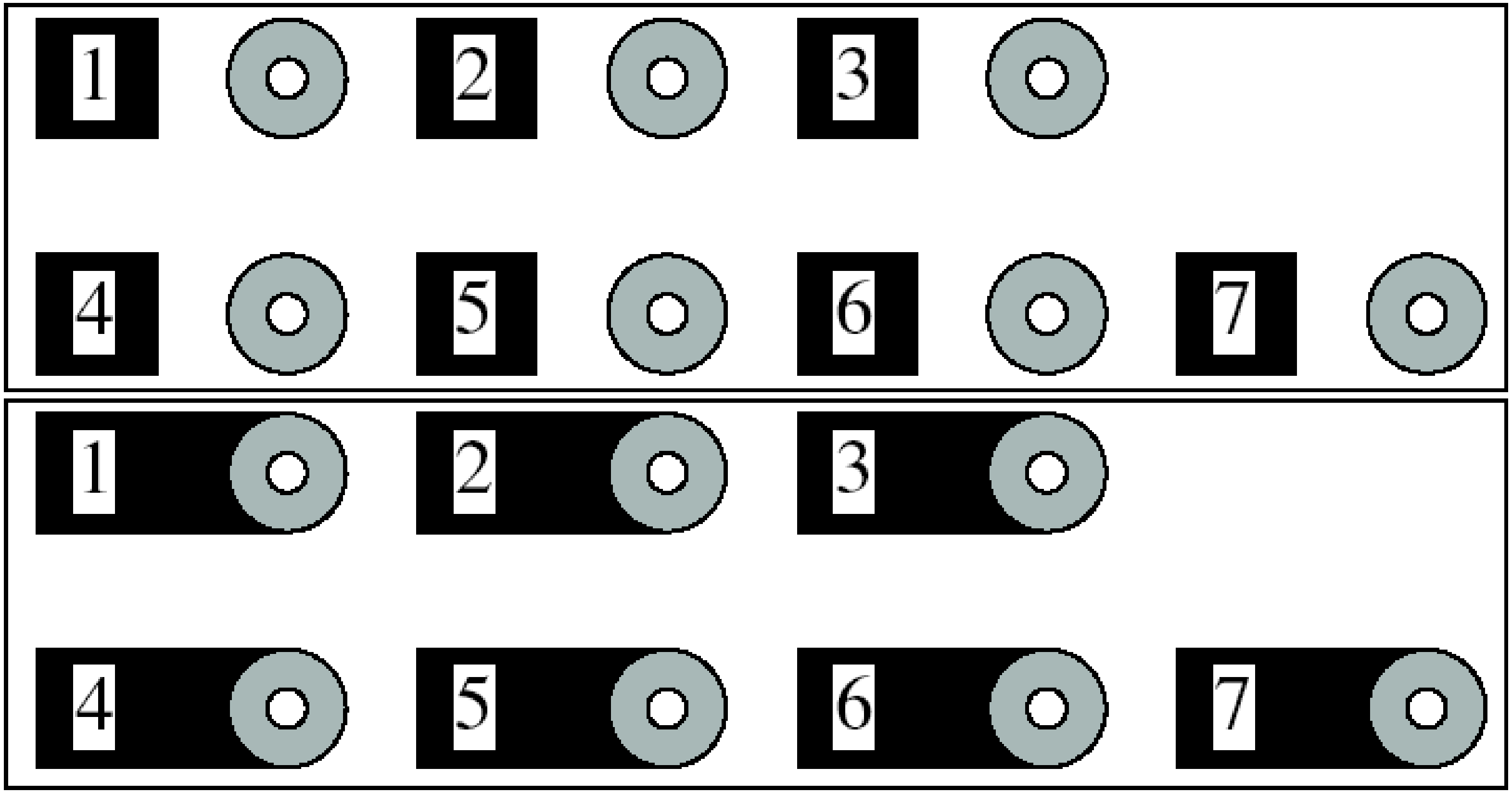


Grouping phenomena in real life



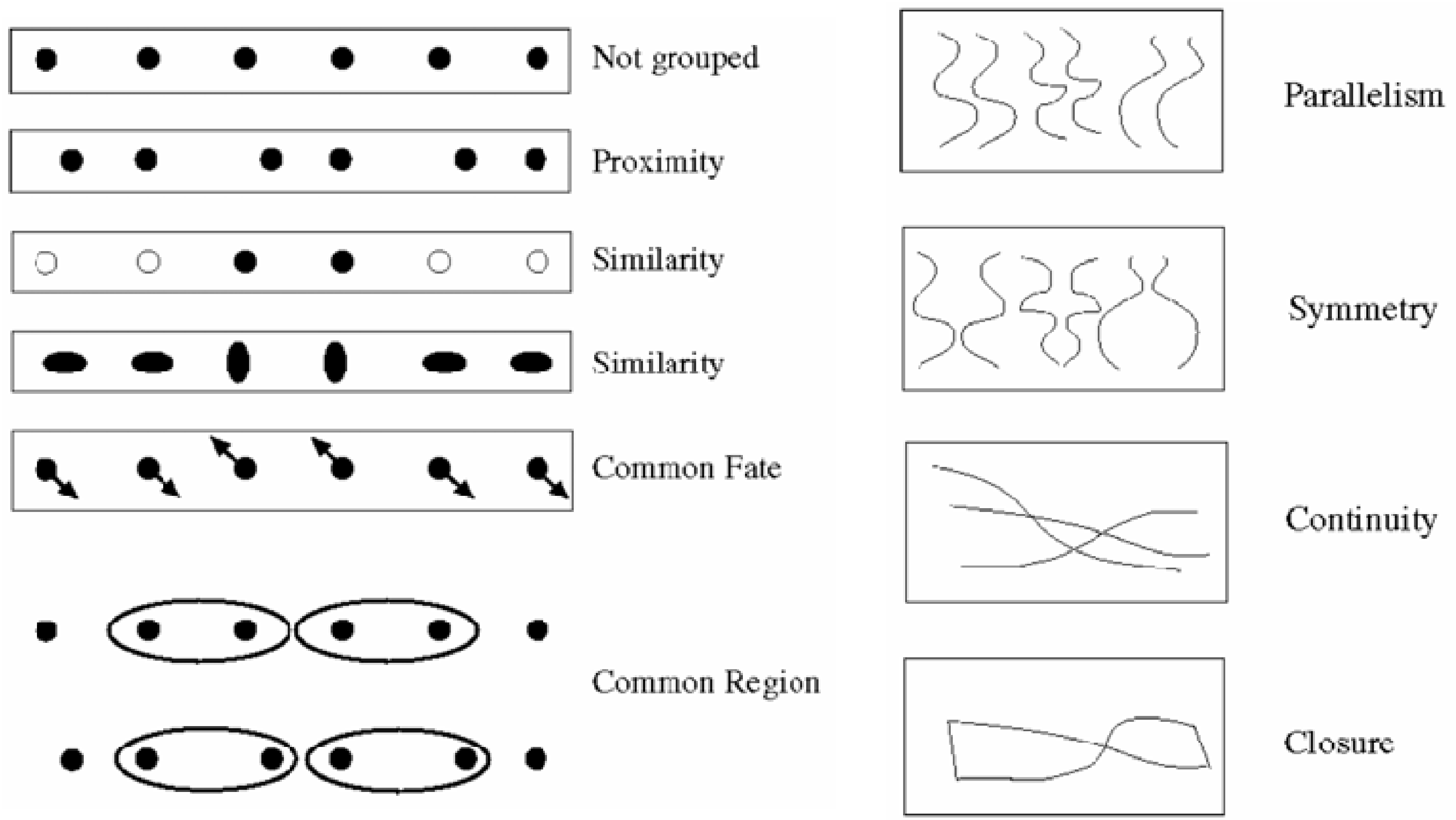
Forsyth & Ponce, Figure 14.7

Grouping phenomena in real life



Forsyth & Ponce, Figure 14.7

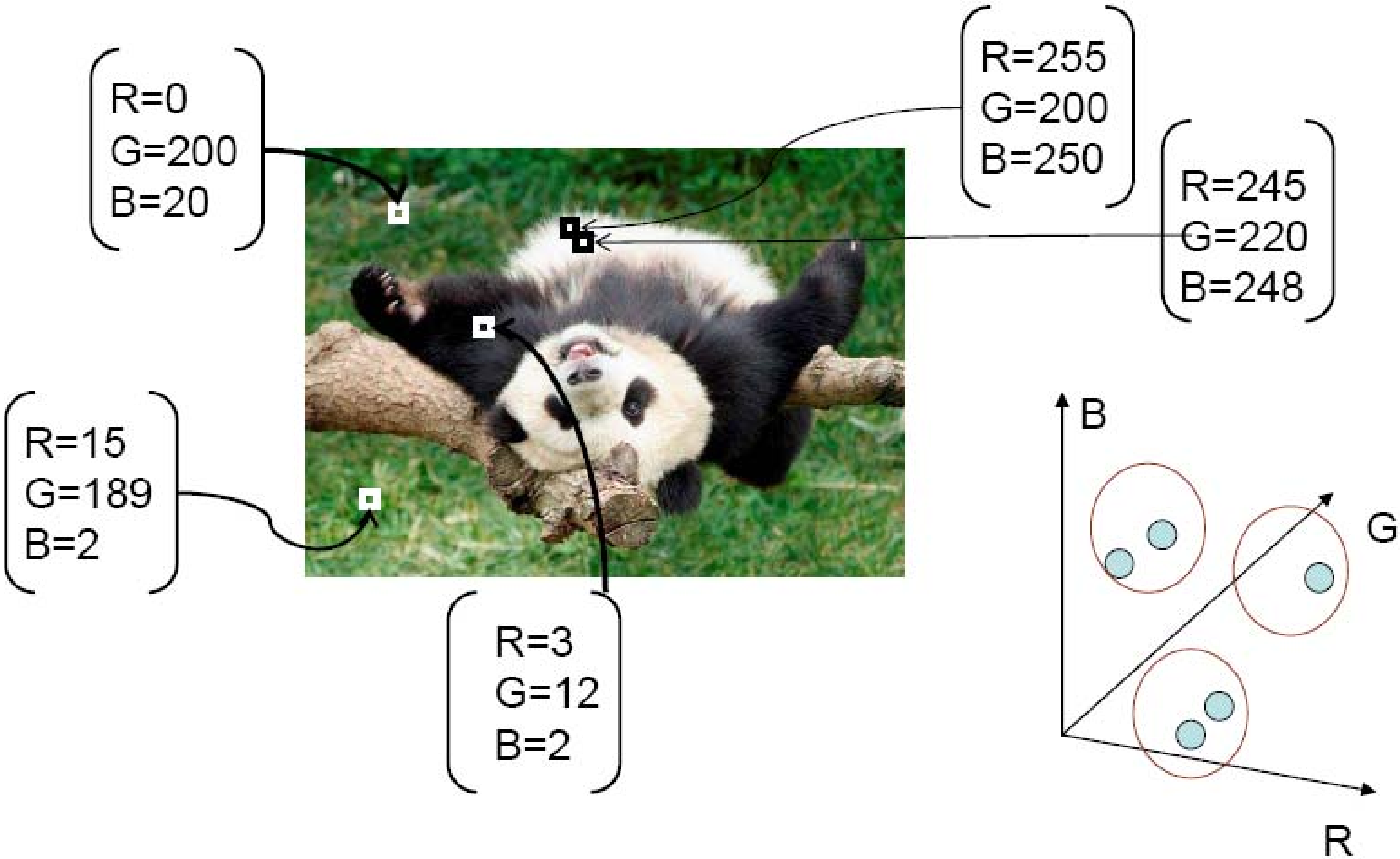
Gestalt factors



- These factors make intuitive sense, but are very difficult to translate into algorithms

Segmentation as clustering

- Cluster similar pixels (features) together



Source: K. Grauman

Segmentation as clustering

- K-means clustering based on intensity or color is essentially vector quantization of the image attributes
    - Clusters don’t have to be spatially coherent

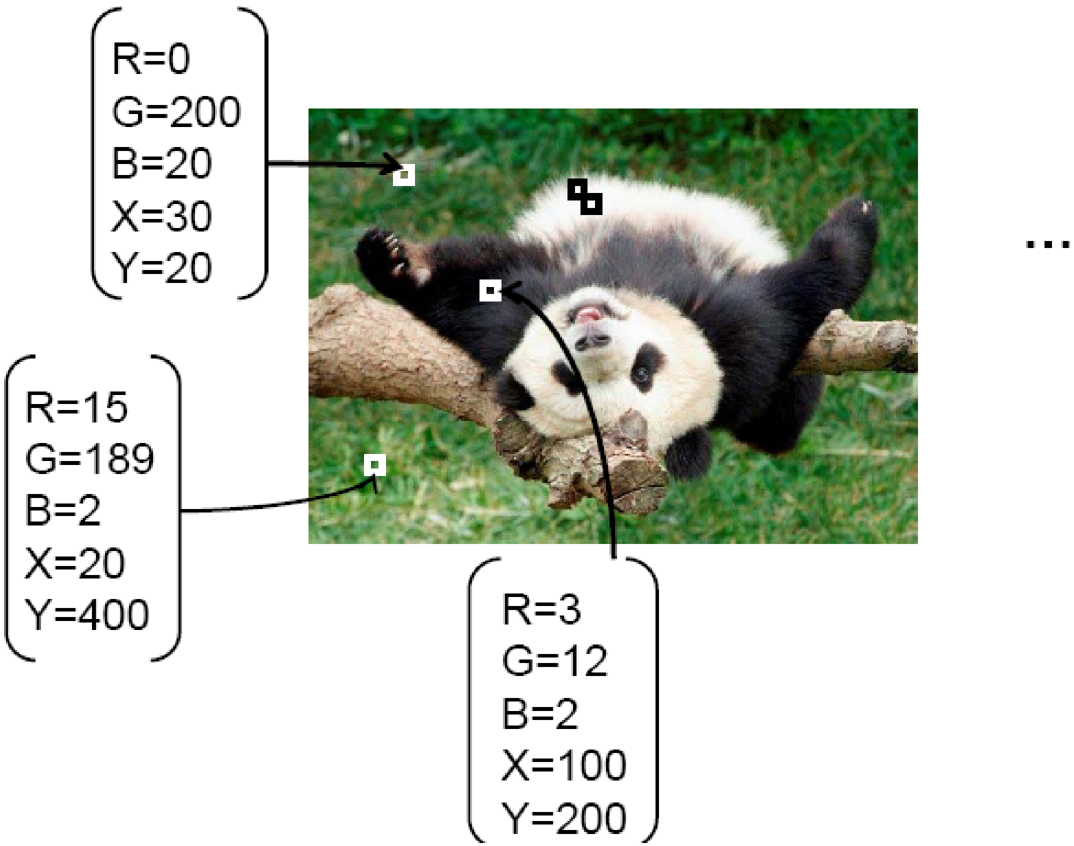
Image

Intensity-based clusters

Color-based clusters

Segmentation as clustering

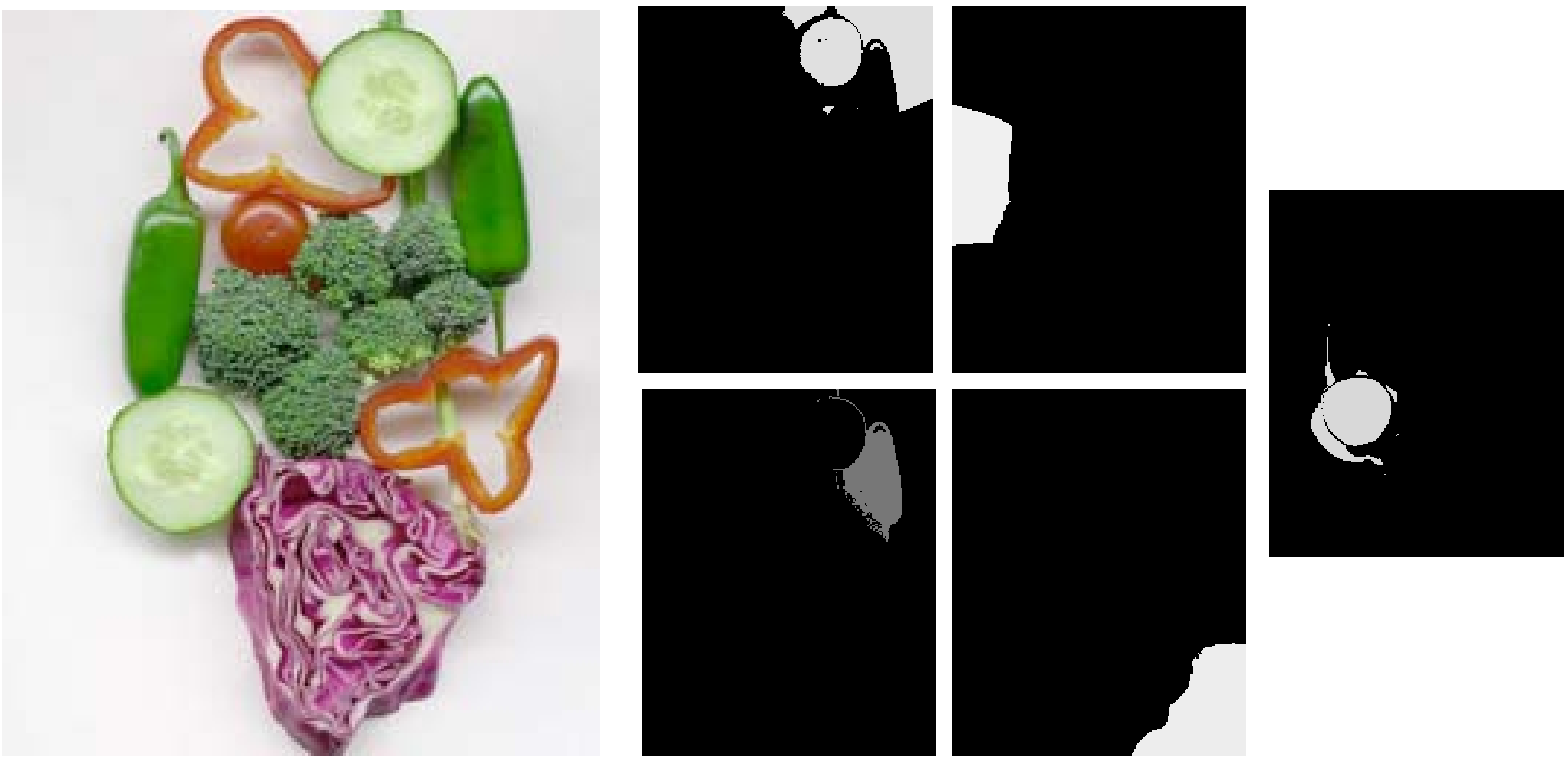
- Cluster similar pixels (features) together



Source: K. Grauman

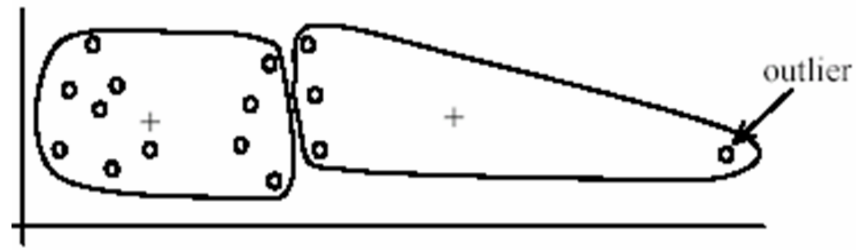
Segmentation as clustering

- Clustering based on (r,g,b,x,y) values enforces more spatial coherence

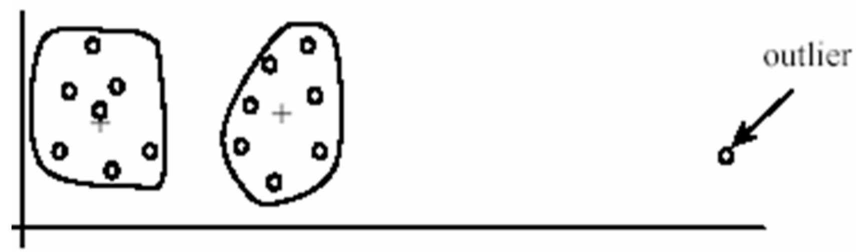


K-Means for segmentation

- Pros
  - Very simple method
  - Converges to a local minimum of the error function
- Cons
  - Memory-intensive
  - Need to pick K
  - Sensitive to initialization
  - Sensitive to outliers
  - Only finds “spherical” clusters



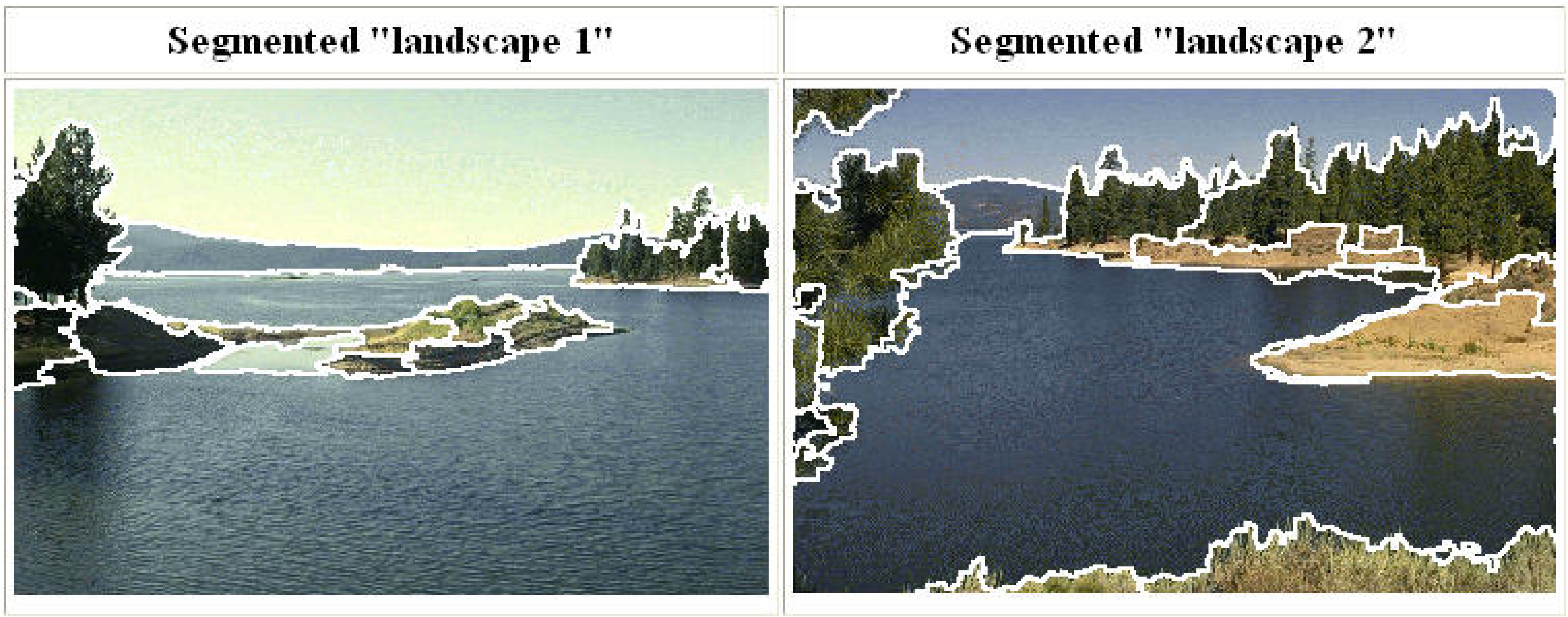
(A): Undesirable clusters



(B): Ideal clusters

Mean shift clustering and segmentation

- An advanced and versatile technique for clustering-based segmentation



http://www.caip.rutgers.edu/~comanici/MSPAMI/msPamiResults.html

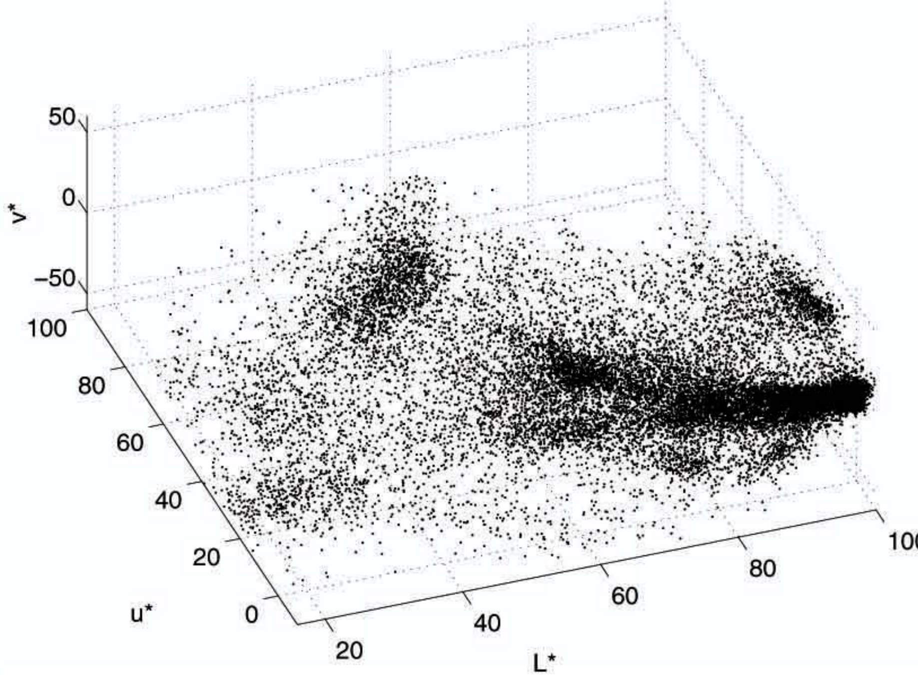
D. Comaniciu and P. Meer, Mean Shift: A Robust Approach toward Feature Space Analysis, PAMI 2002.

Mean shift algorithm

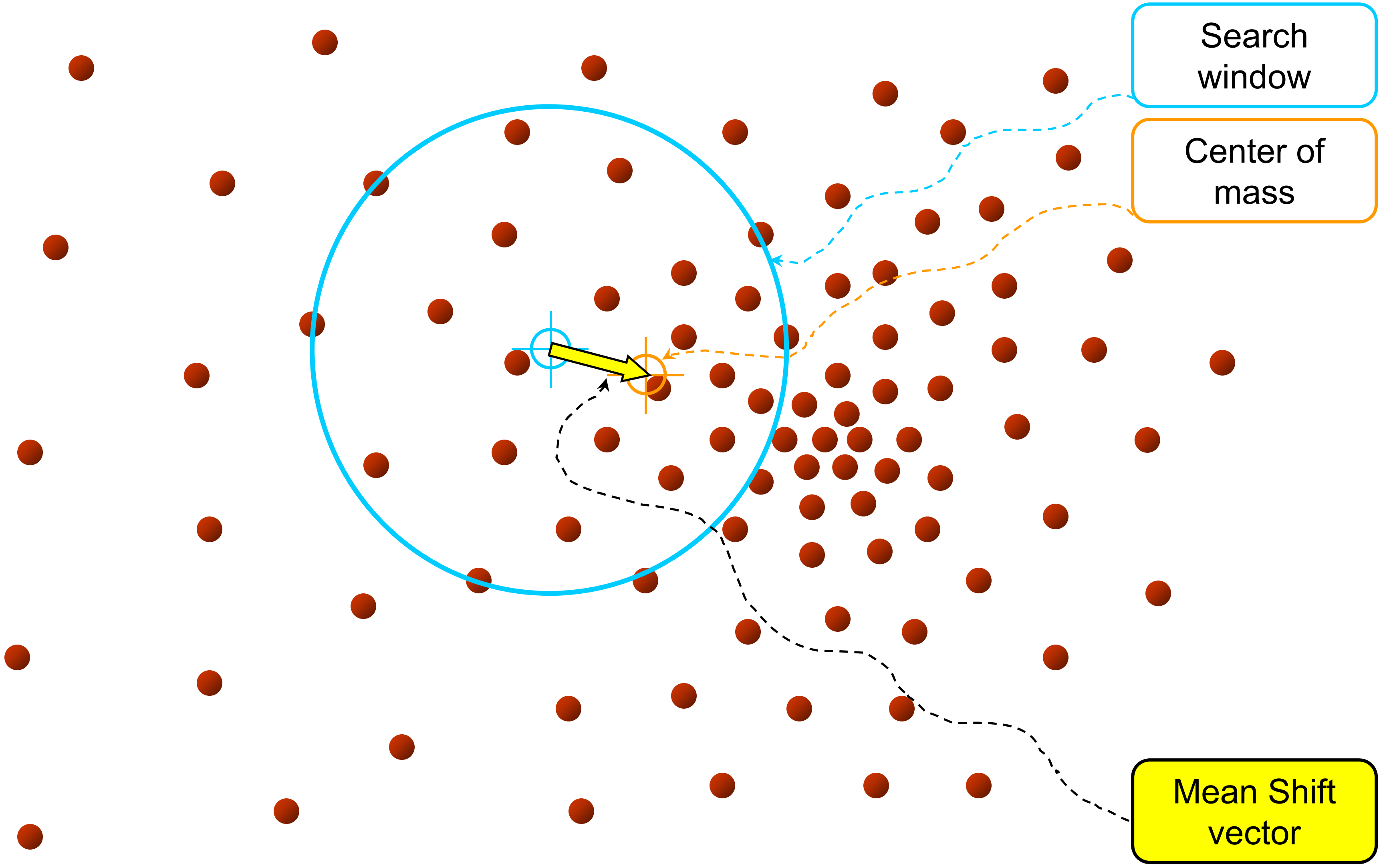
- The mean shift algorithm seeks *modes* or local maxima of density in the feature space

image

Feature space (L*u*v* color values)

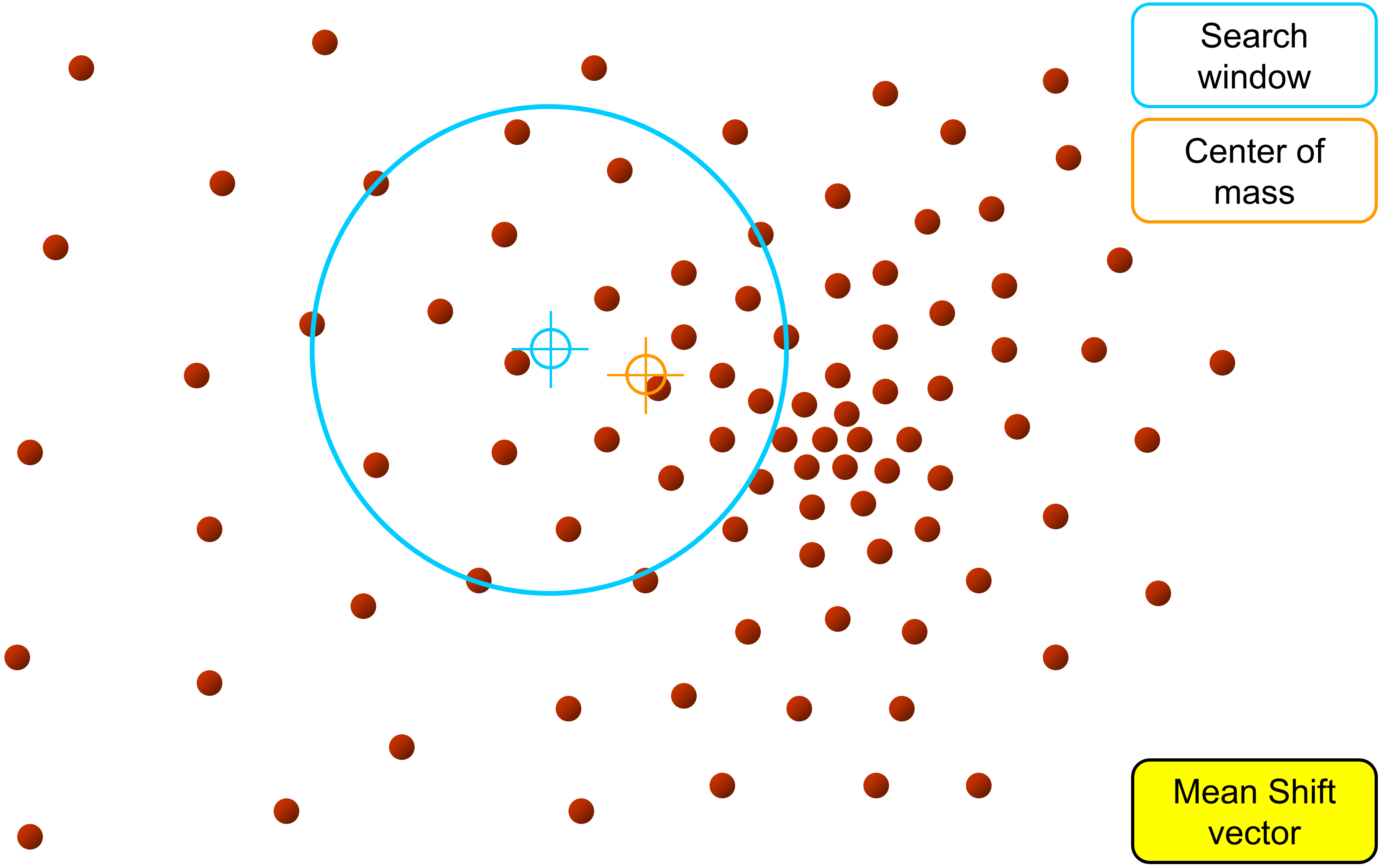


Mean shift



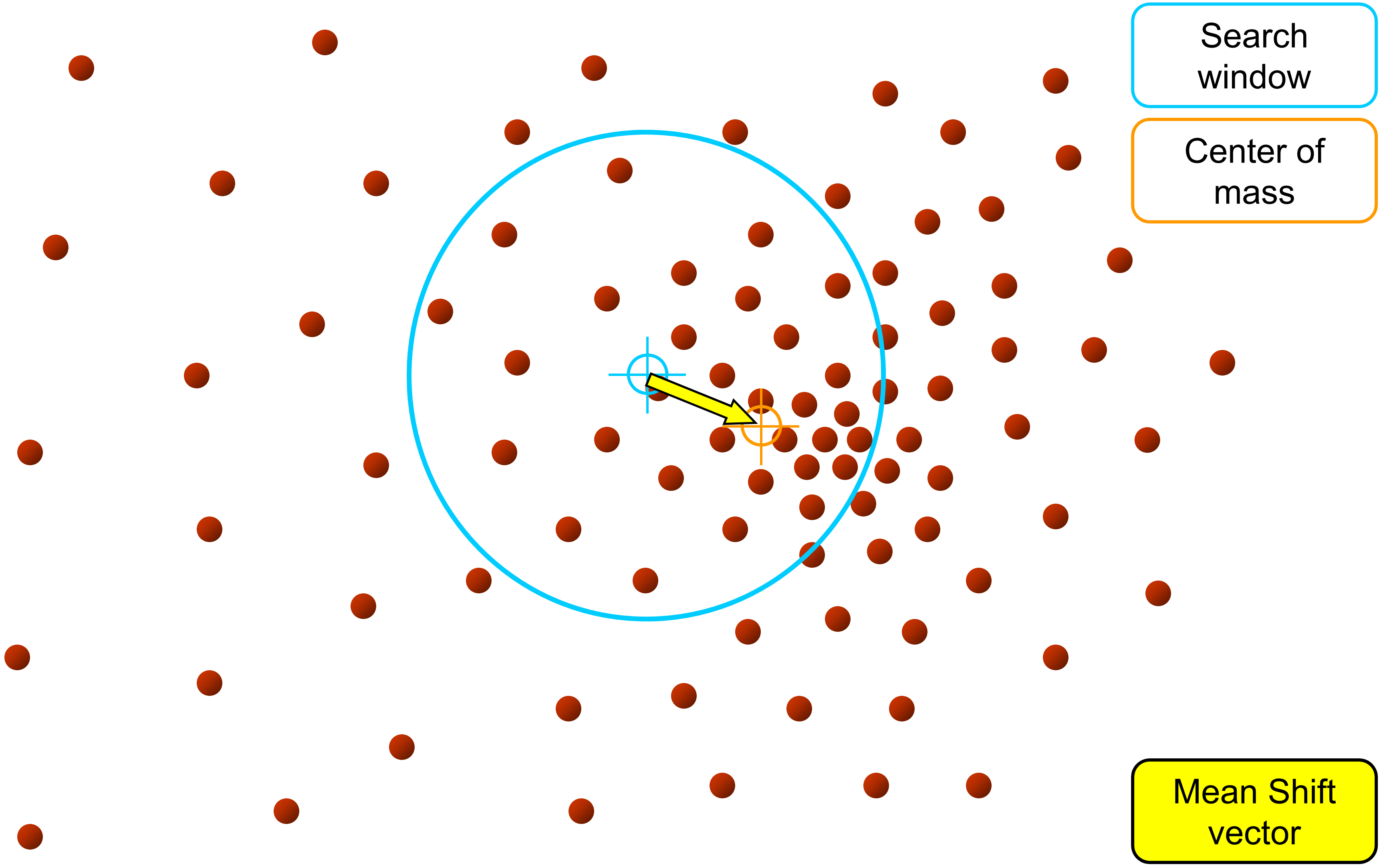
Slide by Y. Ukrainitz & B. Sarel

Mean shift



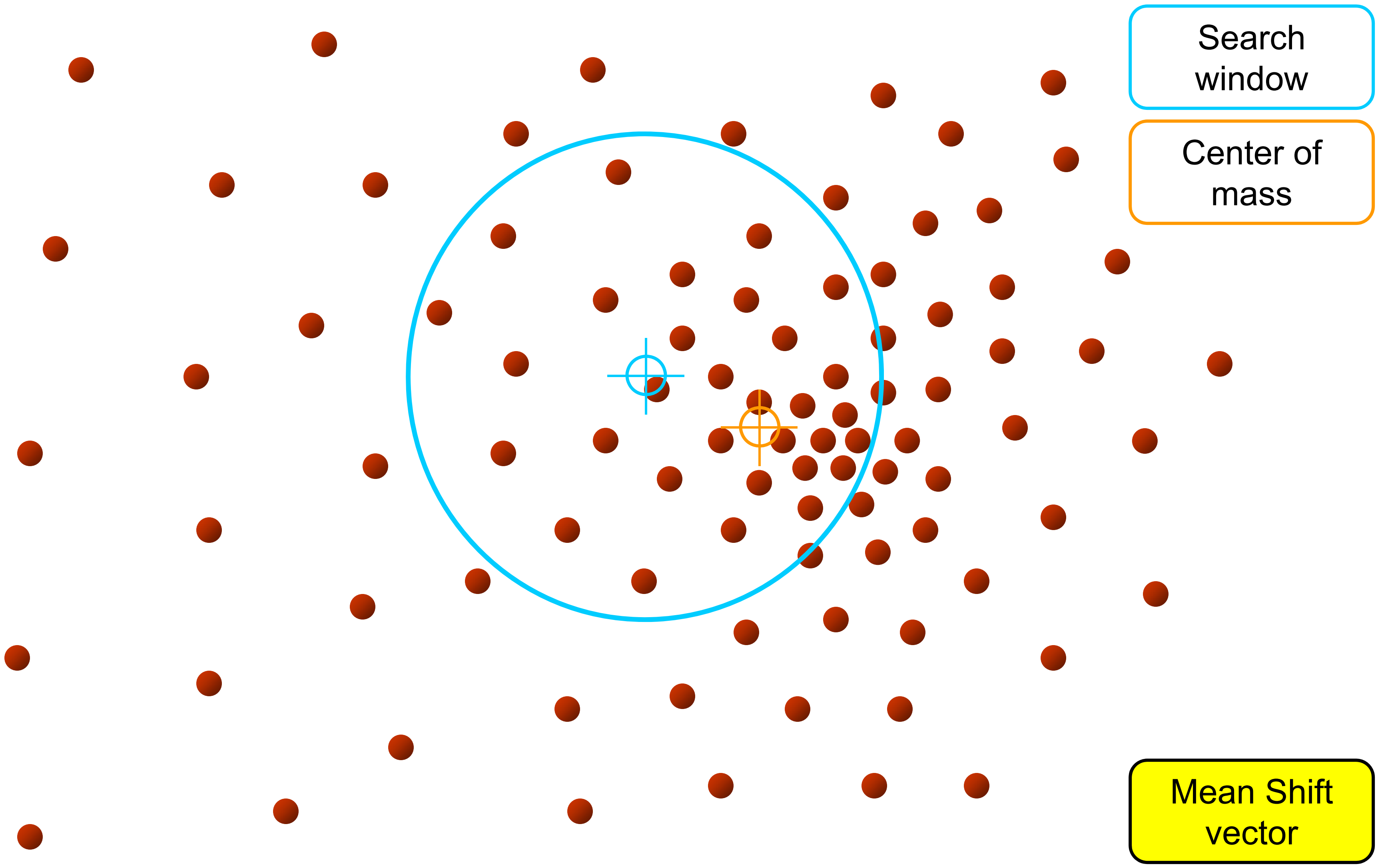
Slide by Y. Ukrainitz & B. Sarel

Mean shift



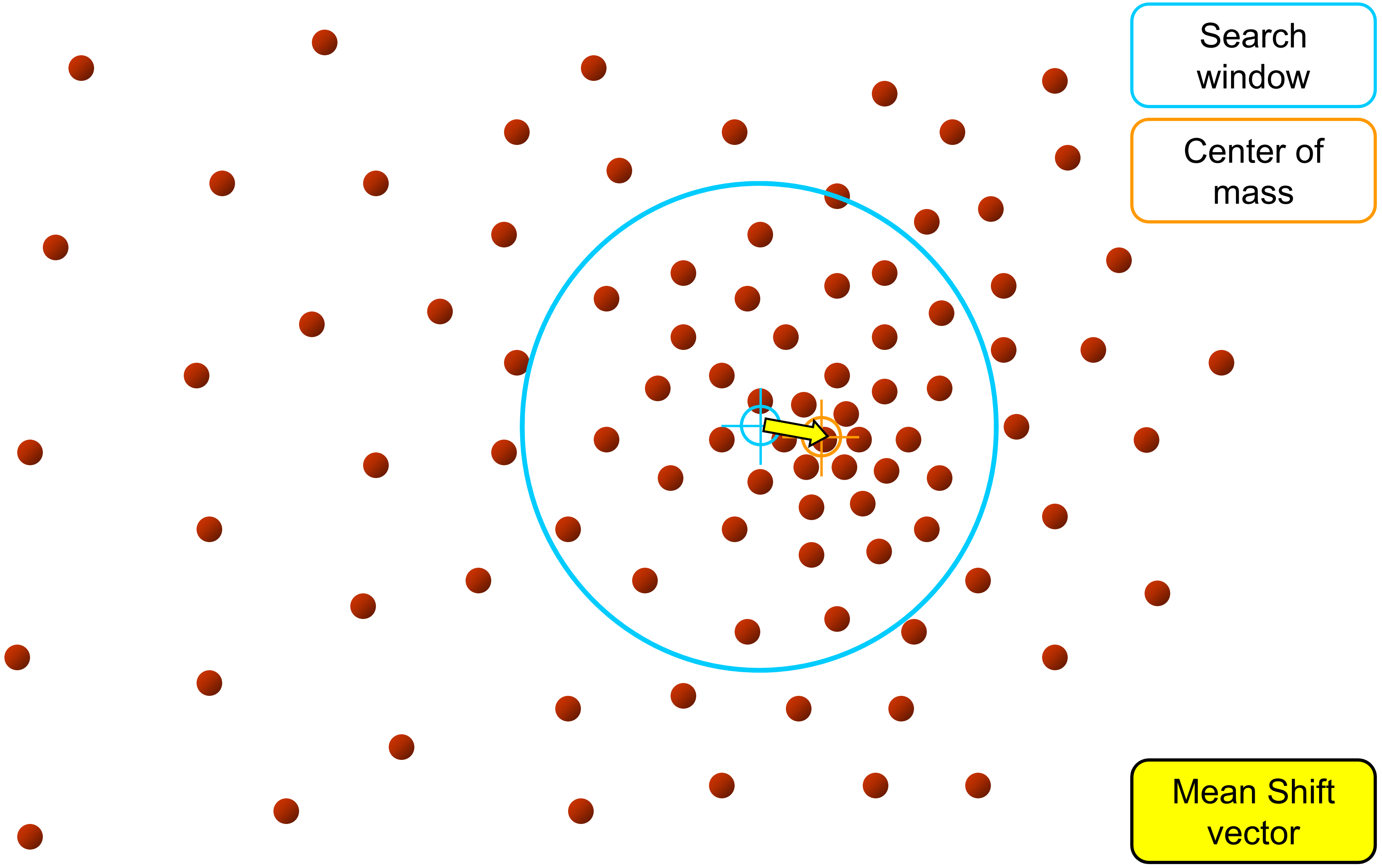
Slide by Y. Ukrainitz & B. Sarel

Mean shift



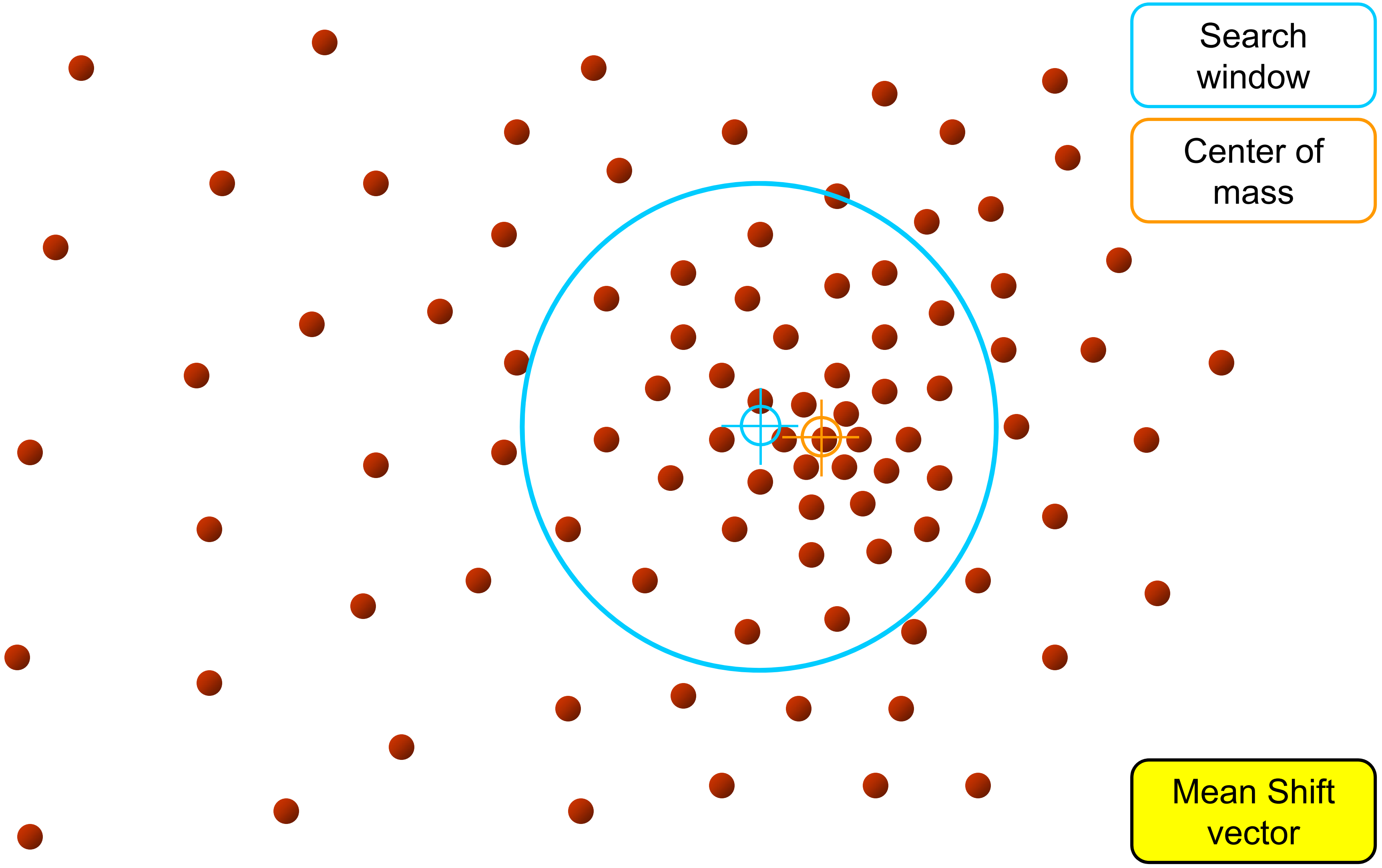
Slide by Y. Ukrainitz & B. Sarel

Mean shift



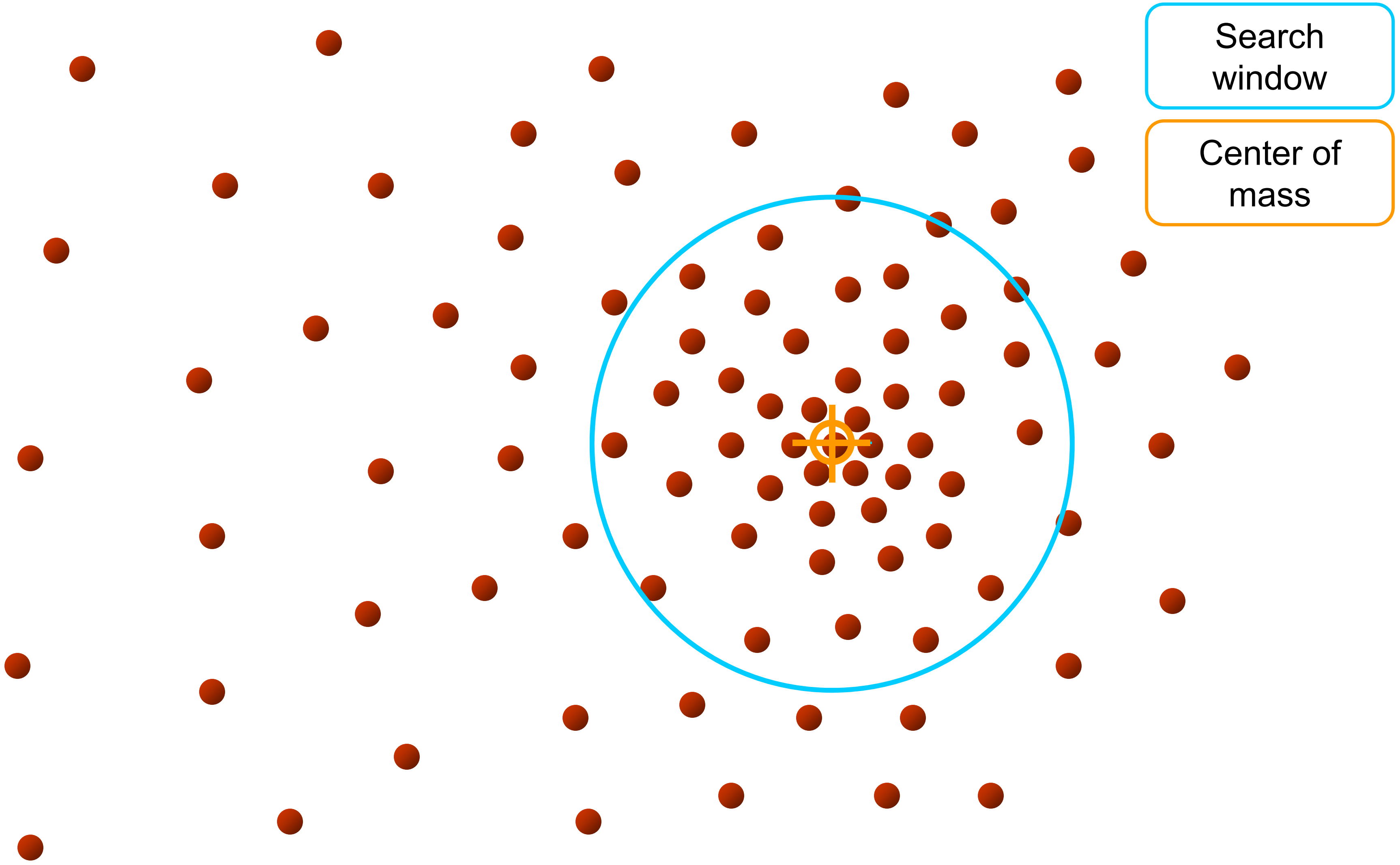
Slide by Y. Ukrainitz & B. Sarel

Mean shift



Slide by Y. Ukrainitz & B. Sarel

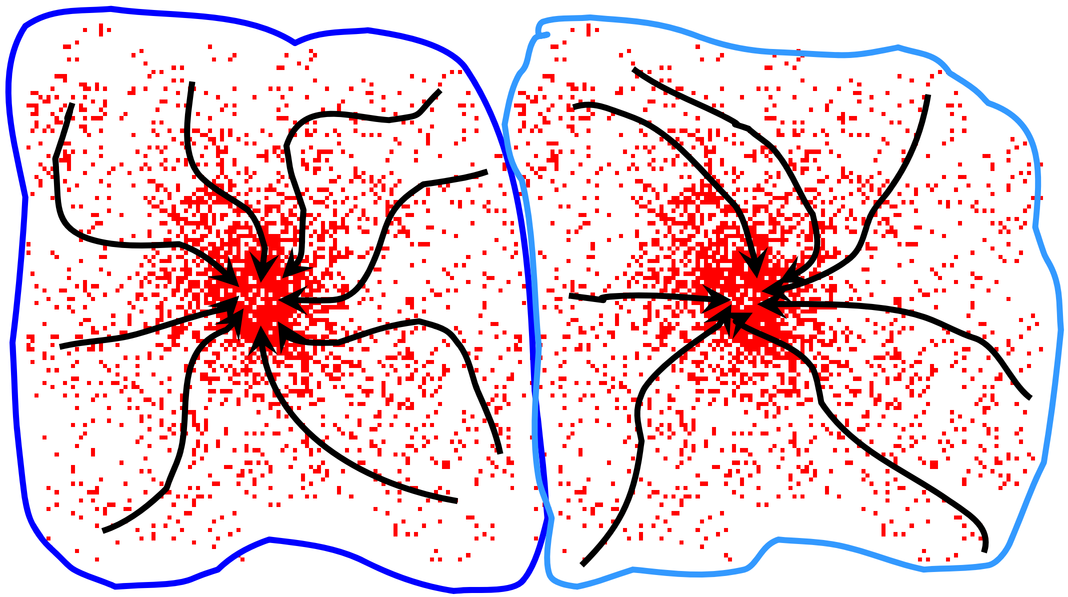
Mean shift



Slide by Y. Ukrainitz & B. Sarel

Mean shift clustering

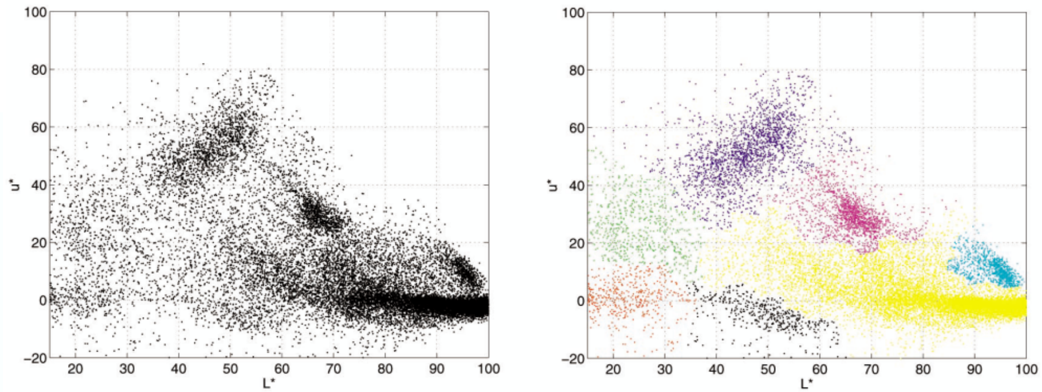
- Cluster: all data points in the attraction basin of a mode
- Attraction basin: the region for which all trajectories lead to the same mode



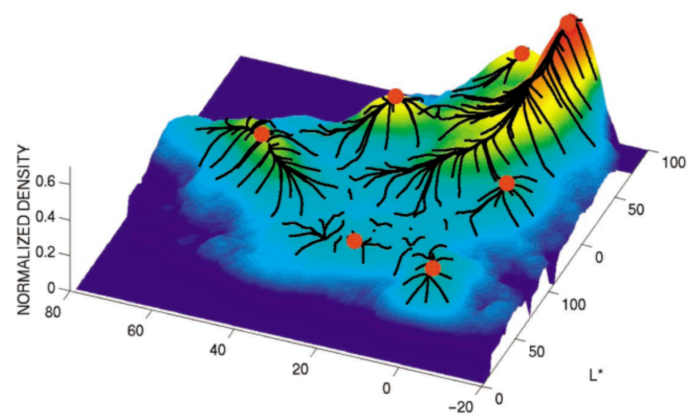
Slide by Y. Ukrainitz & B. Sarel

Mean shift clustering/segmentation

- Find features (color, gradients, texture, etc)
- Initialize windows at individual feature points
- Perform mean shift for each window until convergence
- Merge windows that end up near the same “peak” or mode

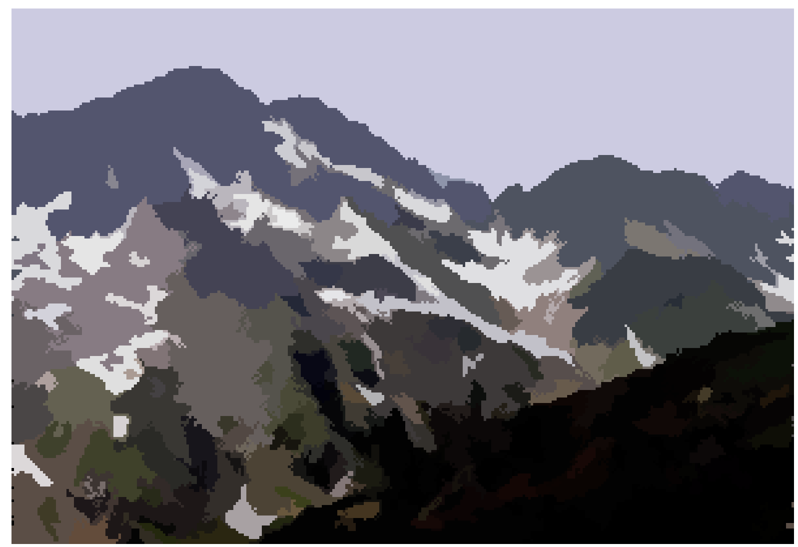


(a) (b)



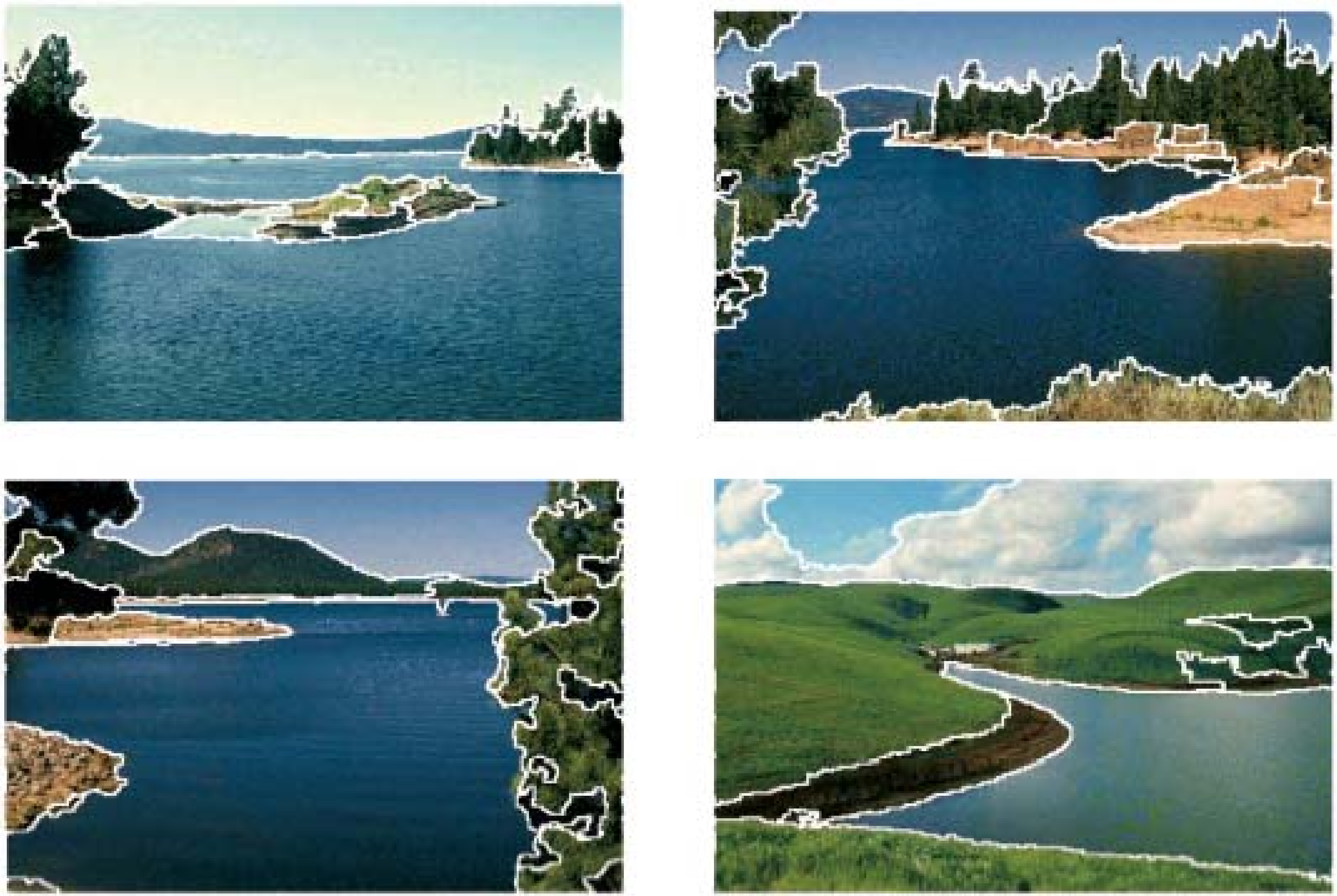
Mean shift segmentation results



http://www.caip.rutgers.edu/~comanici/MSPAMI/msPamiResults.html

More results

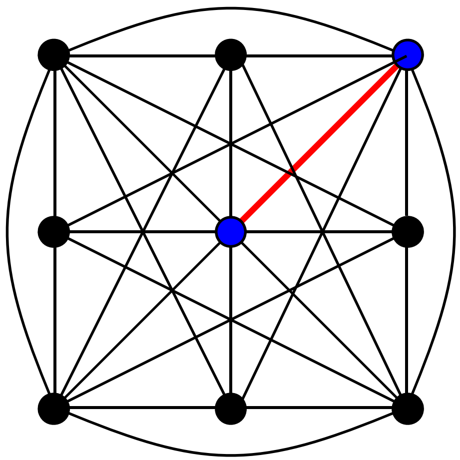


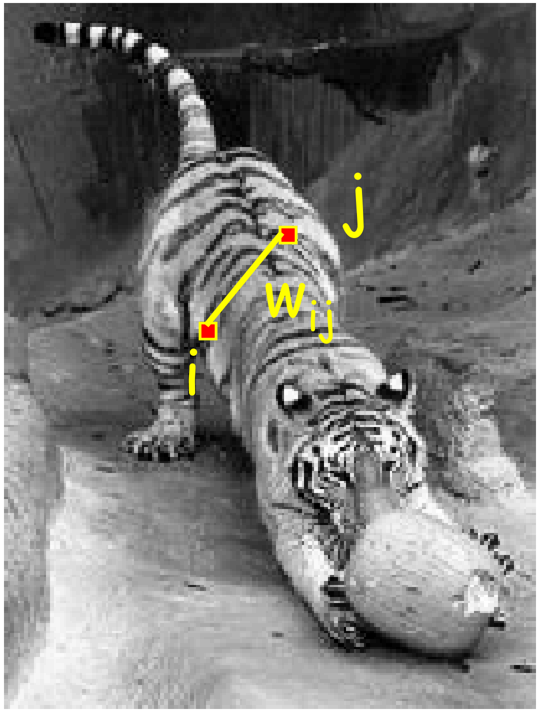
More results

Mean shift pros and cons

- Pros
  - Does not assume spherical clusters
  - Just a single parameter (window size)
  - Finds variable number of modes
  - Robust to outliers
- Cons
  - Output depends on window size
  - Computationally expensive
  - Does not scale well with dimension of feature space

Images as graphs

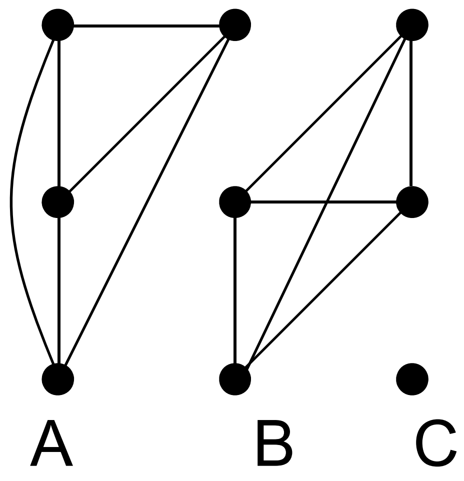




- Node for every pixel
- Edge between every pair of pixels (or every pair of "sufficiently close" pixels)
- Each edge is weighted by the *affinity* or similarity of the two nodes

Source: S. Seitz

Segmentation by graph partitioning



- Break Graph into Segments
  - Delete links that cross between segments
  - Easiest to break links that have low affinity
    - similar pixels should be in the same segments
    - dissimilar pixels should be in different segments

Source: S. Seitz

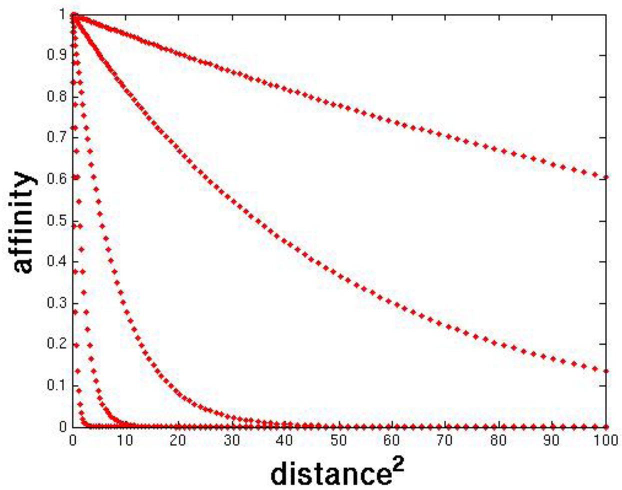
Measuring affinity

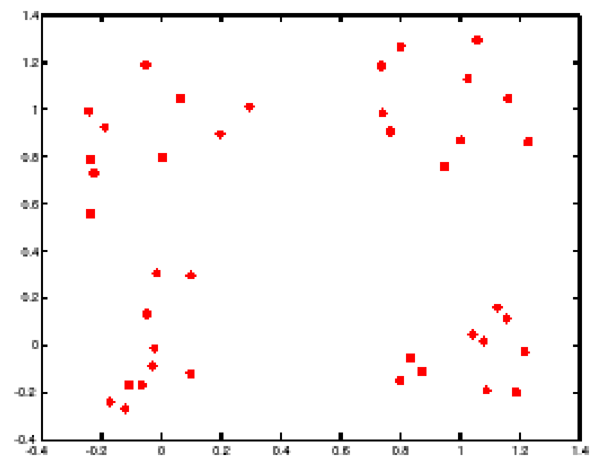
- Suppose we represent each pixel by a feature vector **x**, and define a distance function appropriate for this feature representation
- Then we can convert the distance between two feature vectors into an affinity with the help of a generalized Gaussian kernel:

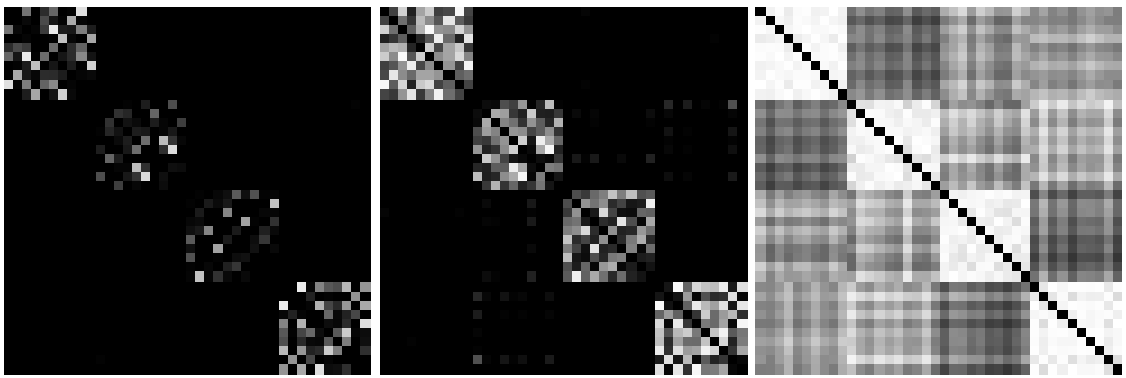
$$\exp\left(-\frac{1}{2\sigma^2}\mathrm{dist}(\mathbf{x}_i, \mathbf{x}_j)^2\right)$$

Scale affects affinity

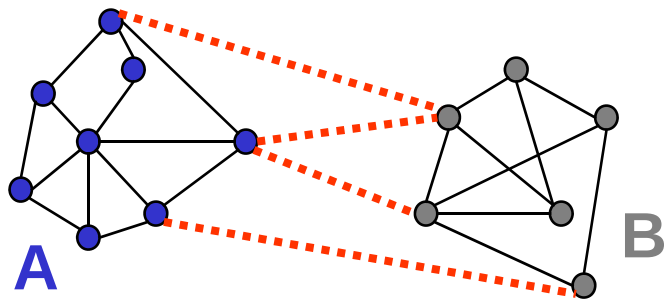
- Small σ: group only nearby points
- Large σ: group far-away points







Graph cut



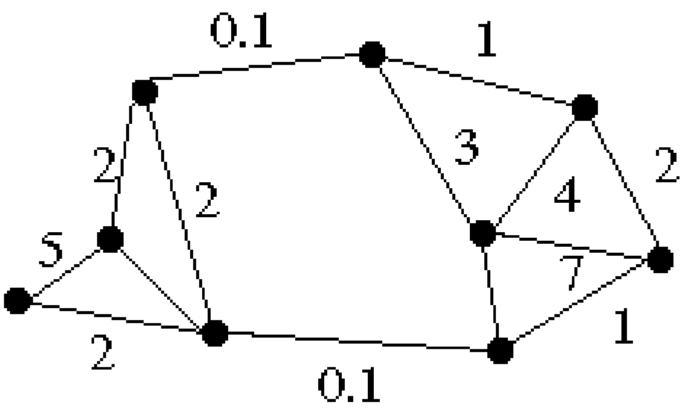
- Set of edges whose removal makes a graph disconnected
- Cost of a cut: sum of weights of cut edges
- A graph cut gives us a segmentation
    - What is a “good” graph cut and how do we find one?

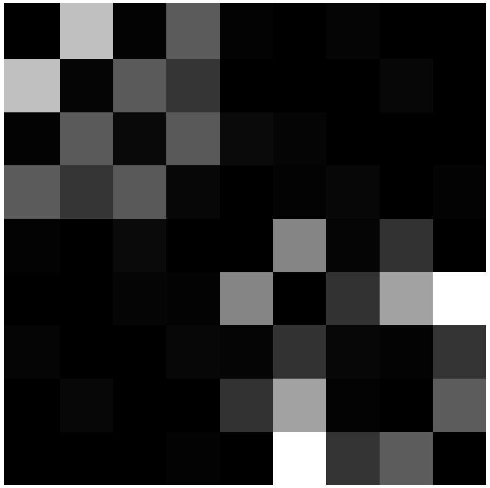
Source: S. Seitz

Minimum cut

- We can do segmentation by finding the *minimum cut* in a graph
  - Efficient algorithms exist for doing this

Minimum cut example

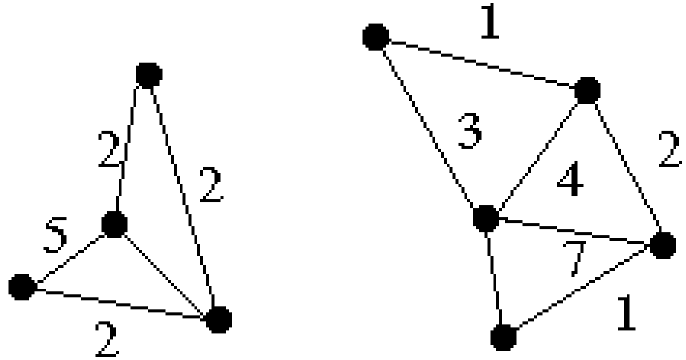


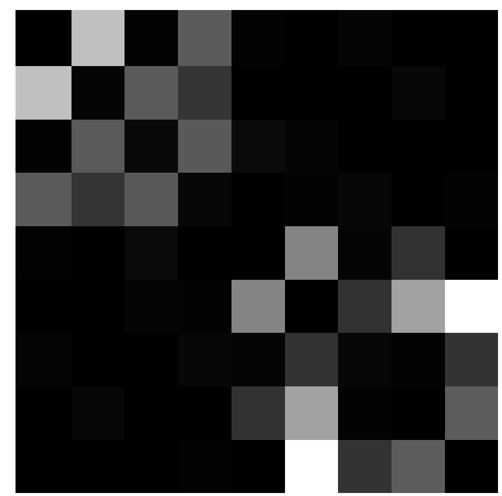


Minimum cut

- We can do segmentation by finding the *minimum cut* in a graph
  - Efficient algorithms exist for doing this

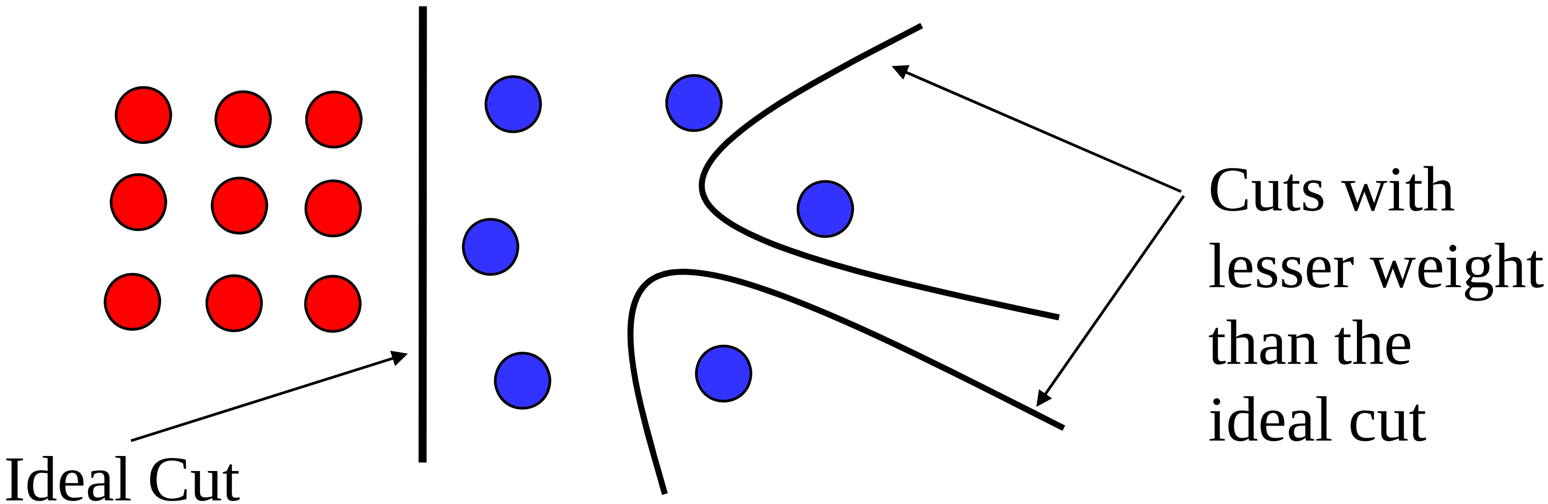
Minimum cut example





Normalized cut

- Drawback: minimum cut tends to cut off very small, isolated components



* Slide from Khurram Hassan-Shafique CAP5415 Computer Vision 2003

Normalized cut

- Drawback: minimum cut tends to cut off very small, isolated components
- This can be fixed by normalizing the cut by the weight of all the edges incident to the segment
- The *normalized cut* cost is:

$$\frac{w(A,B)}{w(A,V)} + \frac{w(A,B)}{w(B,V)}$$

$w(A, B)$ = sum of weights of all edges between A and B

J. Shi and J. Malik. Normalized cuts and image segmentation. PAMI 2000

Normalized cut

- Let W be the adjacency matrix of the graph
- Let D be the diagonal matrix with diagonal entries $D(i, i) = \Sigma_j W(i, j)$
- Then the normalized cut cost can be written as

$$\frac{y^T (D - W) y}{y^T D y}$$

where y is an indicator vector whose value should be 1 in the ith position if the ith feature point belongs to A and a negative constant otherwise

J. Shi and J. Malik. [Normalized cuts and image segmentation.]() PAMI 2000

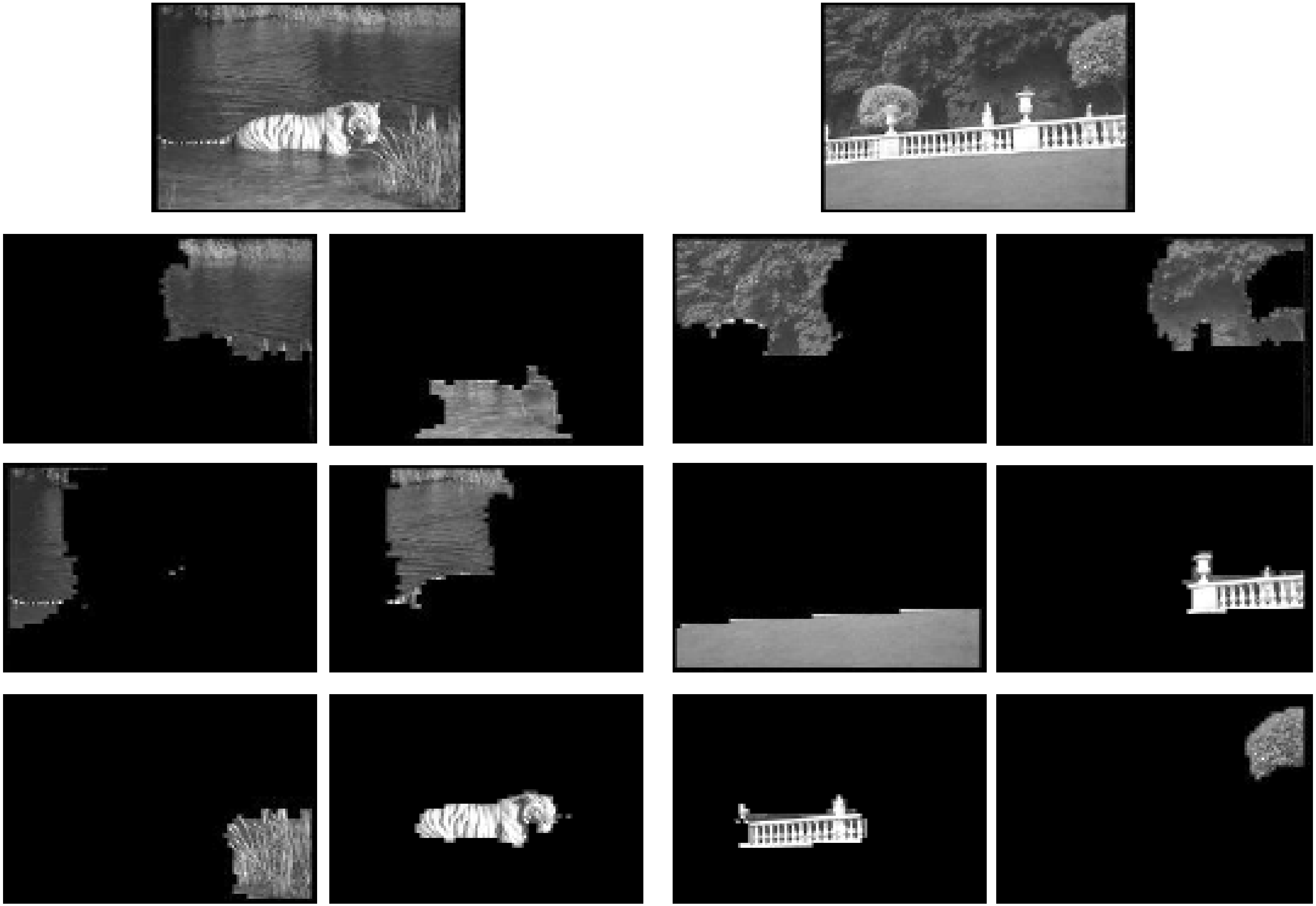
Normalized cut

- Finding the exact minimum of the normalized cut cost is NP-complete, but if we *relax* y to take on arbitrary values, then we can minimize the relaxed cost by solving the *generalized eigenvalue problem* $(D - W)y = \lambda Dy$
- The solution y is given by the eigenvector corresponding to the second smallest eigenvalue
- Intutitively, the ith entry of y can be viewed as a "soft" indication of the component membership of the ith feature
    - Can use 0 or median value of the entries as the splitting point (threshold), or find threshold that minimizes the Ncut cost

Normalized cut algorithm

1. Represent the image as a weighted graph $G = (V,E)$, compute the weight of each edge, and summarize the information in D and W
2. Solve $(D - W)y = \lambda Dy$ for the eigenvector with the second smallest eigenvalue
3. Use the entries of the eigenvector to bipartition the graph
4. Recursively partition the segmented parts, if necessary

Example result

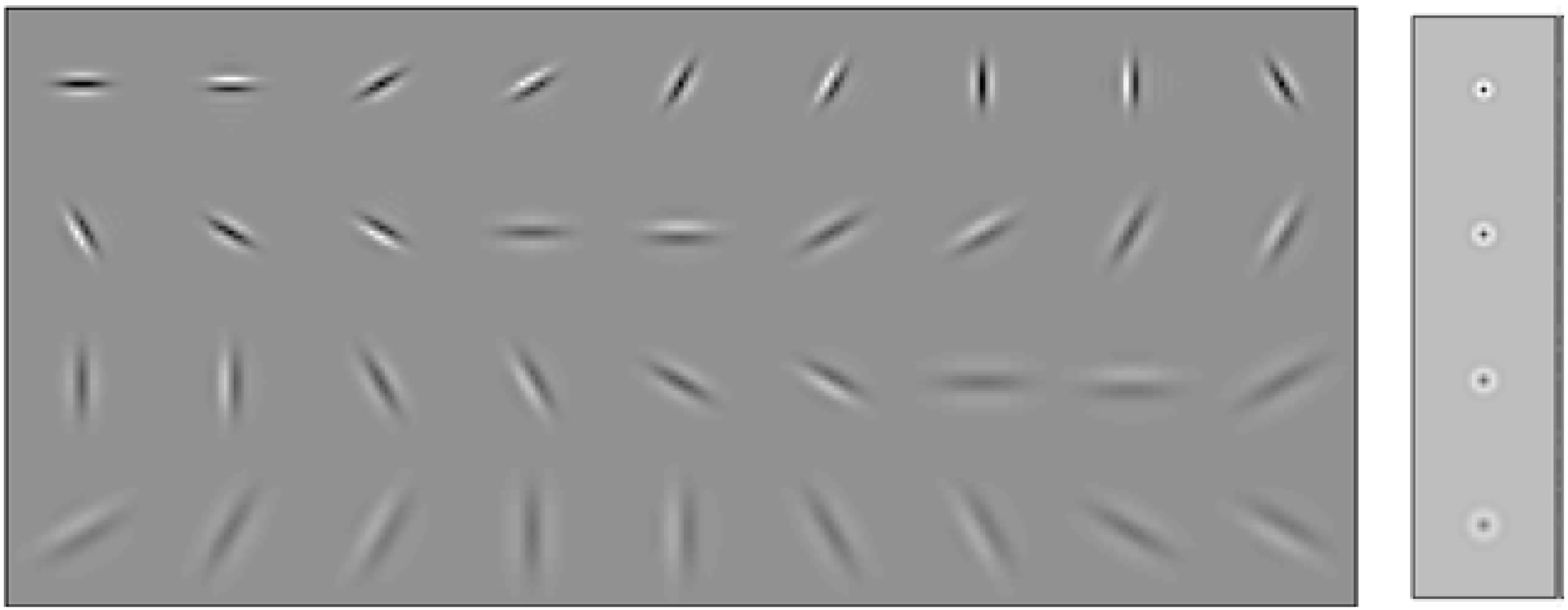


Challenge

- How to segment images that are a “mosaic of textures”?

Using texture features for segmentation

- Convolve image with a bank of filters



J. Malik, S. Belongie, T. Leung and J. Shi. "*Contour and Texture Analysis for Image Segmentation*". IJCV 43(1),7-27,2001.

Using texture features for segmentation

- Convolve image with a bank of filters
- Find textons by clustering vectors of filter bank outputs

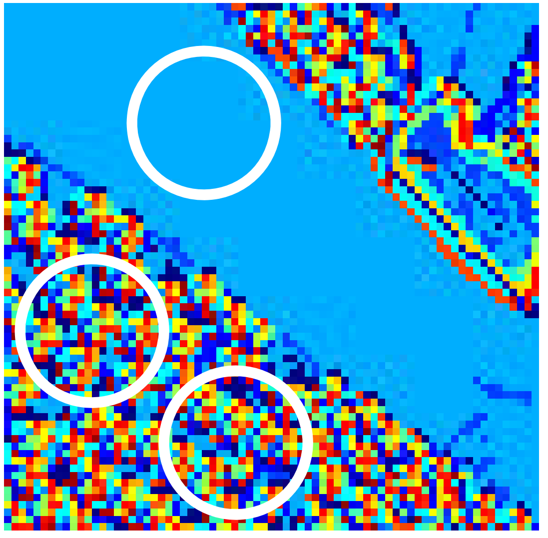
Image

Texton map

J. Malik, S. Belongie, T. Leung and J. Shi. ["*Contour and Texture Analysis for Image Segmentation*"]. IJCV 43(1),7-27,2001.

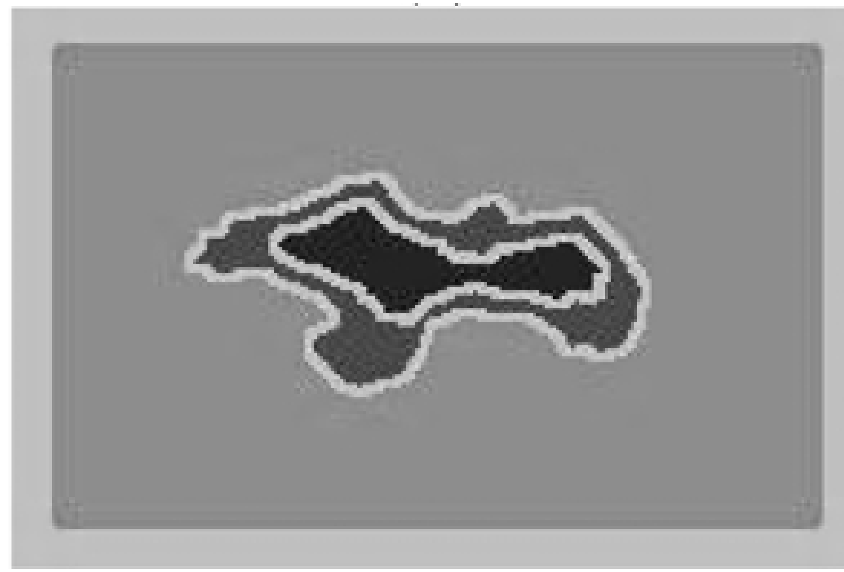
Using texture features for segmentation

- Convolve image with a bank of filters
- Find textons by clustering vectors of filter bank outputs
- The final texture feature is a texton histogram computed over image windows at some “local scale”



J. Malik, S. Belongie, T. Leung and J. Shi. ["*Contour and Texture Analysis for Image Segmentation*"]. IJCV 43(1),7-27,2001.

Pitfall of texture features



- Possible solution: check for "intervening contours" when computing connection weights

J. Malik, S. Belongie, T. Leung and J. Shi. ["*Contour and Texture Analysis for Image Segmentation*"](). IJCV 43(1),7-27,2001.

Example results

Results: Berkeley Segmentation Engine

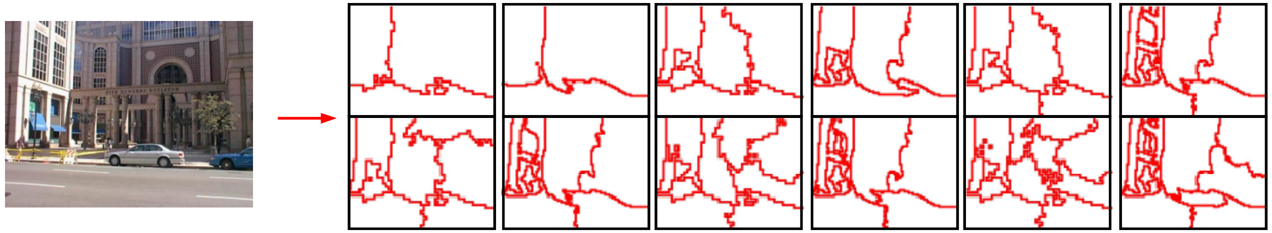
http://www.cs.berkeley.edu/~fowlkes/BSE/

Normalized cuts: Pro and con

- Pros
    - Generic framework, can be used with many different features and affinity formulations
- Cons
    - High storage requirement and time complexity
    - Bias towards partitioning into equal segments

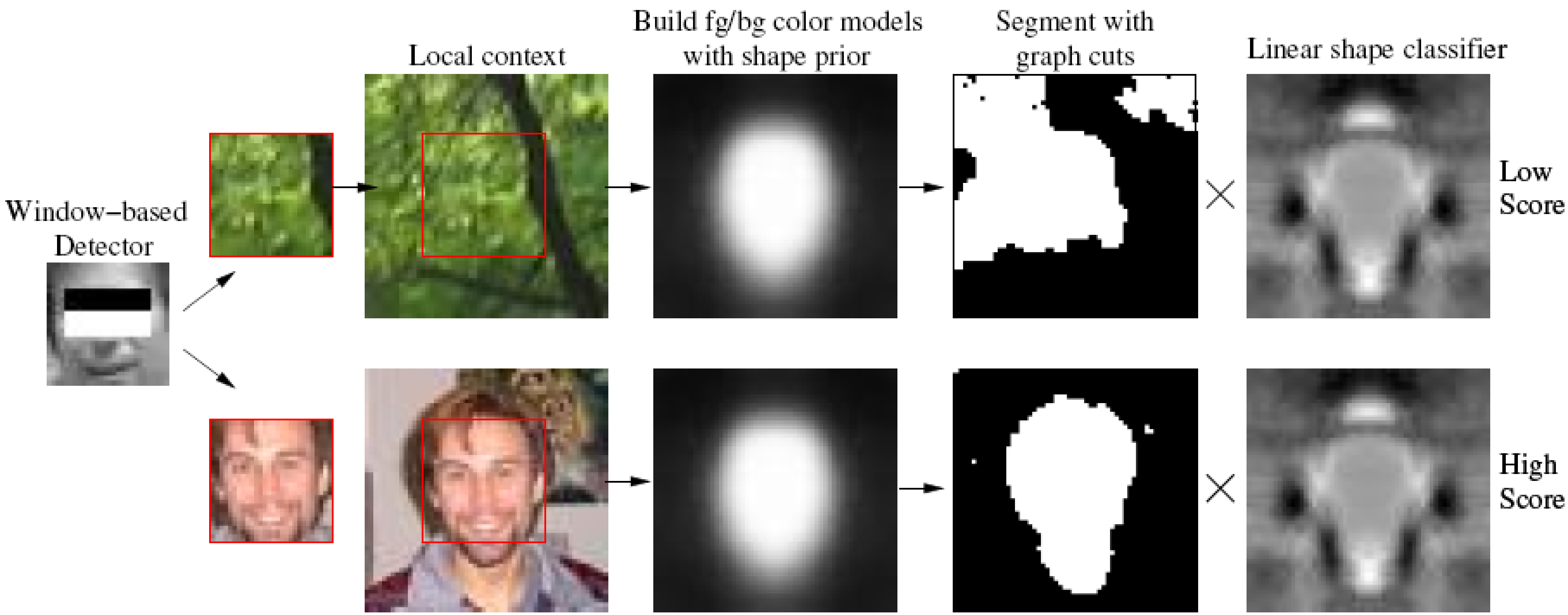
Segments as primitives for recognition?

Multiple segmentations



B. Russell et al., [“Using Multiple Segmentations to Discover Objects and their Extent in Image Collections,”]() CVPR 2006

Object detection and segmentation

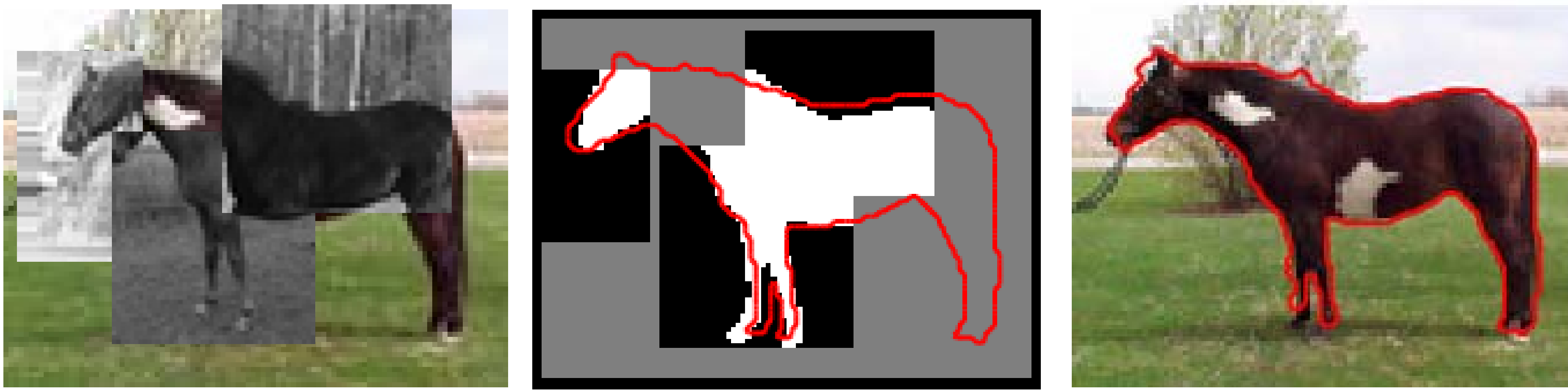


Segmentation energy:

$$E(L) = \sum_i -\log(P(l_i \mid class)) + \alpha \sum_{i,j \in N} \delta(l_i \neq l_j)$$

D. Ramanan, [“Using segmentation to verify object hypotheses,”]() CVPR 2007

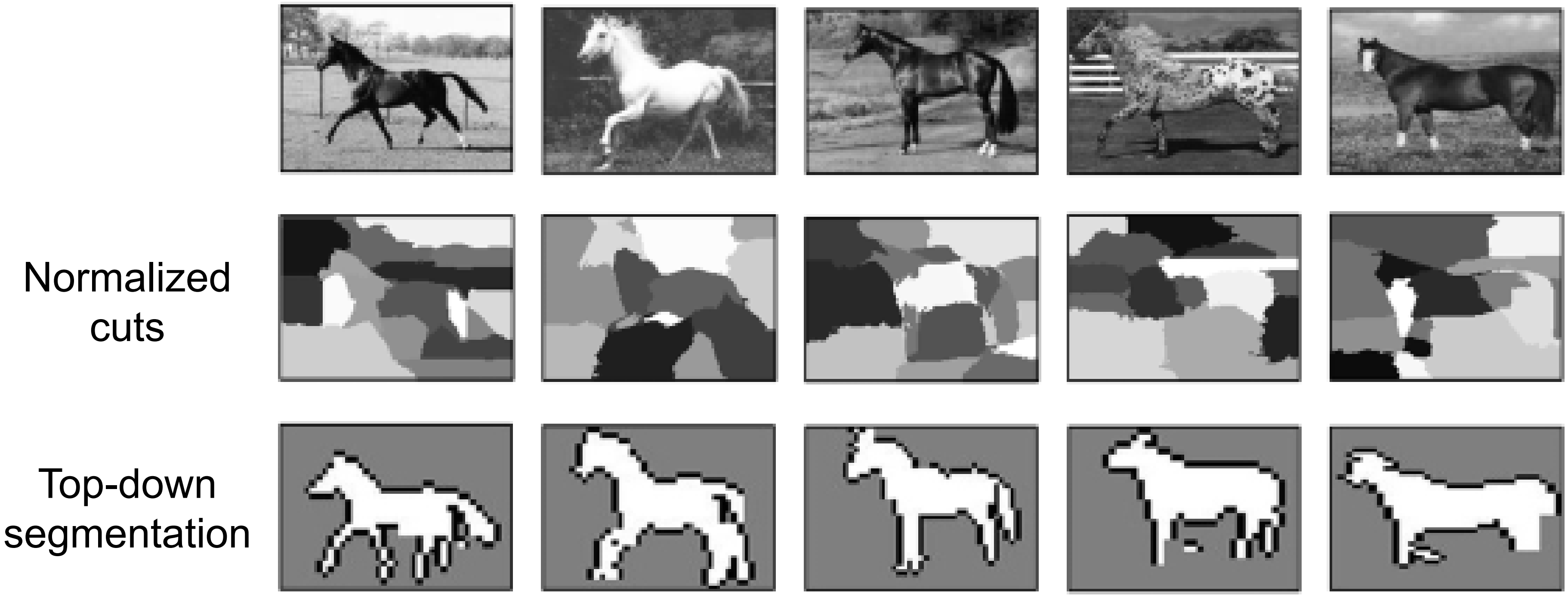
Top-down segmentation



E. Borenstein and S. Ullman, “Class-specific, top-down segmentation,” ECCV 2002

A. Levin and Y. Weiss, “Learning to Combine Bottom-Up and Top-Down Segmentation,” ECCV 2006.

Top-down segmentation



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